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ASPECT-BASED SENTIMENT ANALYSIS IN TURKISH

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DENİZ ÖZKAN

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Approval of the Graduate School of Natural and Applied Sciences, Atilim University.

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ABSTRACT

ASPECT-BASED SENTIMENT ANALYSIS IN TURKISH

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Most customers rely on reviews and comments of other consumers that already purchased and used the products that they intend to purchase. As the sharing opinions and preferences of people on online platforms are widespread, these huge data sources are highly valuable to companies to gather feedback on their products. Therefore, researchers have an essential data mining goal to extract useful information from sentiments. In this thesis, the aim is to perform an aspect-based analysis to determine the sentiment polarity of the reviews for a smart phone using natural language processing techniques in Turkish for the performance, price and camera aspects. The techniques used are data preprocessing, explicit and implicit feature extraction as well as grouping corresponding aspects and lexicon-based sentiment analysis at word-level and word-group level. The evaluations show that the highest values of precision, recall and f1 measure for the aspects examined are found to be 93%, 94% and 93%, respectively. These results reveal that our study has remarkable performance compared to other Turkish aspect-based sentiment analysis studies.

Keywords: Aspect-based Sentiment Analysis, Natural Language Processing, Lexicon-based Sentiment Analysis.

ÖZ

TÜRKÇE HEDEF-TABANLI DUYGU ANALİZİ

Özkan, Deniz
Yüksek Lisans, Yazılım Mühendisliği
Tez Yöneticisi: Dr. Öğr. Üy. Çiğdem Turhan
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Çoğu müşteri bir ürünü satın almayı düşündüklerinde, o ürünü daha önceden satın almış ve kullanmış diğer tüketicilerin inceleme ve yorumlarına güvenir. İnsanların fikir ve tercihlerini online platformlarda paylaşması yaygınlaştıkça, bu devasa bilgi kaynağı şirketlerin ürünleri hakkında geri bildirim alabilmeleri için çok değerli hale gelmiştir. Bu yüzden araştırmacılar, veri madenciliği ile duygulardan yararlı bilgileri ayrıştırmak gibi önemli bir amaç edinmişlerdir. Bu tezin hedefi, bir akıllı telefon hakkındaki Türkçe incelemelerin duygu sınıflarının belirlenmesi için doğal dil işleme kullanılarak; performans, fiyat ve kamera hedefleri bazında hedef-tabanlı duygu analizini gerçekleştirmektir. Kullanılan teknikler veri ön işlenmesi, açık ve kapalı özellik çıkarımı ve bunların ilgili hedeflere gruplanması, kelime ve kelime grupları seviyesinde sözlük tabanlı duygu analizidir. Sonuçlar, incelenen hedefler için en yüksek kesinlik, duyarlılık ve F1 ölçümü değerlerinin sırasıyla %93, %94 ve %93 olduğunu göstermiştir. Bu sonuçlar bizim çalışmamızın, diğer Türkçe hedef tabanlı duygu analizi çalışmalarıyla karşılaştırıldığında, kayda değer bir performansa sahip olduğunu ortaya çıkarıyor.

Anahtar Kelimeler: Hedef-Tabanlı Duygu Analizi, Doğal Dil İşleme, Sözlük-Tabanlı Duygu Analizi

To my precious mother and lovely husband...

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CHAPTER 1
INTRODUCTION

When purchasing an item, people usually trust the suggestions of other people and ask for recommendations. With the emergence of Web 2.0, websites provide user generated content, ease of use and interactivity with the end user. In Web 2.0, unlike Web 1.0, people do not only read the content and also are keen on contributing to the content via sharing opinion on online platforms such as e-commerce web sites and social media [1]. According to a survey [2], users generally perform an online search about a product before buying it, and online reviews about the product affect their opinion. As the sharing opinions and preferences of people on online platforms are foreseen to be common in the close future, O'Reilly and John Battelle [3] defined these huge data sources as more valuable for companies to get feedback on their products. Using the customer reviews, they can monitor their brand reputation, analyze which aspects of their product are liked or disliked by consumers and examine the reasons for their criticisms.

Since Web 2.0 provides the huge data sources, extracting useful information from sentiments on textual resources has become an essential data mining goal for researchers. The term Semantic Web which was named as Web 3.0, was introduced with by Berners-Lee [4] to refer to a web of content where the semantics can be analyzed by machine learning or natural language processing methods [5]. The task of sentiment analysis aims to specify the polarity of sentiment in text. In other words, text is classified according to the sentiment category. The text which is classified can be a word, phrase, sentence or a document. The polarity can be predicted as three categories which are positive, negative and neutral or multi-variant scale as the strength of sentiment expressed in the text.

Although Sentiment analysis is crucial in terms of data mining, document level analysis is inadequate to understand the sentiment of the text correctly. Because, in many cases, people talk about many aspects which belong to the same item and they have a different view about each of these aspects. This often happens in reviews

about products in e-commerce websites or in discussion forums. An example of a smartphone review which was gathered from “Hepsiburada” website is “Evet fiyat pahalı ama en hoşuma giden tarafı şarjı eski telefonları gibi değil uzun süre gidiyor”. Classifying the example review as positive or negative, the overall analysis of the review produces a wrong sentiment. Because, the word “pahalı” refers to the aspect “fiyat” negatively, while the aspect “şarj” is referred as positively in terms of the sentiment [6]. With the aim of gaining a deeper understanding, the technique aspect - based sentiment analysis (ABSA) is developed which identifies various aspects in terms of the domain of the text and determines the corresponding sentiment for each one. In other words, instead of classifying the overall sentiment of a text into positive or negative, ABSA allows to associate specific sentiments with different aspects of a product. Aspects can be referred by explicit and implicit features. If a feature or any of its synonyms refer to the aspect directly in a sentence, the feature is called an explicit feature in this sentence. On the contrary, the implicit features are the features that imply the aspect indirectly. Grouping explicit and implicit features for each aspect are completed in two tasks. First, feature words should be specified from the reviews, and then the feature words should be grouped into their corresponding aspects. Grouping the features, especially implicit features, is the difficult task needs comprehensive work for increasing the accuracy of the ABSA’s results.[7] The results of ABSA are more fine grained, interesting and accurate because it examines more closely the information behind the text which can be at word level, word group level or sentence level. This information is crucially important for marketing to create a seamless customer experience and increase customer retention. Because, according to research by American Express [8], customers are willing to spend more money with a company that delivers an excellent service.

In the literature, there are three main concepts for aspect-based sentiment analysis which are machine learning (ML), lexicon-based and hybrid systems which are combinations of both. Machine learning approach includes two main types which are supervised and unsupervised learning. While in the supervised approach, the system learns a classification model from the training data using one of the common classification algorithms such as SVM, Naive Bayes, Logistic Regression, or KNN, the unsupervised approach does not require a classification model to be taught. While

machine learning approaches may work more accurately than lexicon-based methods, if there is not a huge amount of data in the given domain, lexicon-based methods perform with sufficient accuracy with a small data set in the domain. Generally, online product reviews are about many different domains and the size of this type of data is not huge. Therefore, lexicon-based approach is suitable for the semantic analysis of online product reviews [9].

In this thesis, the aim is to perform an analysis to determine the sentiment polarity of the reviewers towards various aspects of iPhone which is a smart phone developed by Apple using natural language processing. The techniques used are data preprocessing, explicit and implicit feature extraction as well as grouping corresponding aspects, lexicon-based sentiment analysis at word-level and word-group level because of the advantages mentioned above. Most of the current studies on aspect-based sentiment classification typically focus on reviews about movies, restaurants, blogs, news and tweets written in the English language. On the other hand, there are very limited studies conducted to classify the aspect-based sentimental analysis for reviews in Turkish language which has an complex informal text structure different than English, therefore making the use of Turkish a major challenge for this thesis.

The background information on the fundamentals of these concepts, the design and implementation of aspect-based sentiment analysis used in the thesis, testing and evaluation of the analysis results with extensive discussions, as well as the conclusion of the study are given in detail consecutively in the following sections.

CHAPTER 2
LITERATURE REVIEW

This thesis aims to classify sentiments in online comments comprised of humans' complaints or complements in the Turkish language with aspect-based sentiment analysis. Much of the existing research on textual information processing have focused on mining and retrieval of factual information, e.g., information retrieval, Web search, text classification, text clustering and other text mining and natural language processing tasks. A limited number of studies have been done on sentiment analysis ł in recent years. People care about others' feelings whenever they need to make decisions. This is not only correct for people but also for organizations. One of the main reasons for the lack of study about opinion mining and sentiment analysis is the fact that there was limited text containing sentiments before the World Wide Web [10]. Before the Web, when a person needed to decide about something, he/she typically asked for ideas from friends and families. If an organization wanted to know the ideas or feelings of the people about its products and services, polls or surveys were performed. In recent years, the emergence of Web 2.0 augments the size of user-generated content on the internet rapidly. Many organizations give increasingly high importance to sentiment analysis and opinion mining of online review for effective organizational decision making [11]. However, finding opinion contents and monitoring them online can still be a challenging task because a great number of diverse contents exist, and each content may also have a high volume of text including opinions or sentiments. In most cases, sentiments are hidden in long forum posts and product reviews on the e-commerce web sites. For individuals, reading relevant contents as well as finding, summarizing and organizing opinion-related sentences into useful forms from those contents are remarkably difficult. Therefore, the need for automated opinion discovery systems has emerged. The number of studies about sentiment analysis which is also called opinion mining has increased because of this requirement. Additionally, since it is extremely valuable for real-life practices, both academic research and industrial applications seem to embrace automated opinion discovery systems increasingly in recent years [12].

Therefore, the sentiment analysis which is a crucial part of the automated opinion discovery systems has been studied since the early 90s [9], [13]-[20].

This section provides some information about studies on ABSA in the literature. With this aim, it is organized in turn as defining the problem of ABSA, reviewing similar studies of other researchers on ABSA, natural language processing and feature extraction in the Turkish language and others.

2.1 The Problem of Aspect-Based Sentiment Analysis

Aspect-based sentiment analysis model is first defined as the attributes that belong to an object and the opinions that have been expressed in a sentence which are about the attributes. Secondly, this model specifies whether the opinions are positive, negative or neutral. While the objects are also called as targets, the attributes are also called as aspects, as well as features. An object can be one of the following items: product, service, individual, organization, event, topic, etc. In a product review, the model specifies product features which are written in the comment and assigns a value which means that the feature is implied positively, negatively or neutral to each feature. As an example, in the sentence, "Bu telefonun pil ömrü çok kısa." the aspect is "pil ömrü" of the "telefon" object and the sentiment is negative. Many organizations in the marketing area need aspect level analysis in order to increase the product quality. Understanding liked and disliked features of the product by people helps organizations to improve disliked features and maintain the liked features. Such specific information is not discovered by sentiment classification [15].

The following review about iPhone which was taken from our data set is used to introduce the problem: "(1)Yaklaşık bir haftadır kullanıyorum telefonu. (2)Çok beğendim! (3)Hızlı bir telefon kullanımı çok rahat.. (4)Güncelleme ile ilgili hic bir zaman sorun yapmaz. (5)Bataryasi mükemmel. (6)Fotoğraf kalitesi çok iyi değil bence. (7)Fiyat olarak pahalı ama eğer maddi olarak sıkıntı vermeyecekse hiç düşünmeyin." There are several sentences which describe sentiments in this review. Sentences (2), (3), (4), (5), (6) carry positive meaning, while sentences (7) include negative meaning. Sentence (1) which has no sentiment was ignored in this analysis. When the review is examined in more detail, all expressed sentiments which refer to

different features or objects are noticed. The sentiment in sentence (2) is about the iPhone as a whole, so, sentence (2) was ignored in the feature based analysis. The "hız" feature in sentence (3) which has a positive meaning refers to the "performans" aspect implicitly. In addition, in sentence (4) and (5), the implicit feature "güncelleme" and "batarya" refers to the "performans" aspect positively. The negative sentiment in sentence (6) which is about the "fotoğraf" feature refers to the "kamera" aspect implicitly. The extraction of implicit and explicit features is a crucial task on this detailed level analysis [16]. In the sentence (7), the feeling is negative directly about the "fiyat" aspect. As a result, the negative or positive tag of the overall comment is incorrect because of the different sentiments placed in the comment. With this example; the general overview of the problems related to of aspect-based sentiment analysis is presented. In the next section, other researches about aspect-based sentiment analysis are reviewed.

2.2 Aspect-Based Sentiment Analysis of Text

One of the subtasks of sentiment analysis is opinion mining which is extracting attitudes and feelings in the text specifying it as either positive or negative according to the sentiment reflected in the text. Sentiment analysis is also expressed as subjectivity analysis which aims to define feeling, emotions and attitudes that are explained by natural language. The main aim of analyzing sentiment or opinion words in the sentences and the documents is to predict the sentiment orientation as positive, negative or neutral [6]. The analysis and automatic extraction of semantic orientation can be expressed by diverse terms which are sentiment analysis [17], subjectivity [21], opinion mining [22], analysis of stance [23], appraisal [24], emotion [25] and aspect-based also called feature based [26] .

Large number of research on ABSA from text is available. Most of these studies explain sentiment as positive, negative or neutral [27]-[30]. There are also some studies [31], [32] that extract positive or negative sentiment strength with predicting the human ratings on a scale. For example, sentiment in the text is classified as a number in the scale between 0-10 which corresponds to exceedingly negative or exceedingly positive. Also some recent approaches are developed to detect multiple emotions and aspects from single sentences [26], [33]-[35]. While these methods are

usually applied on large texts such as newspaper and movie reviews, some research are studied on short texts such as Twitter corpora to perform ABSA [36]-[39]. The rapid proliferation of e-commerce websites on Web 2.0 leads to huge amount of costumer reviews about product information which makes ABSA of online customer reviews a hot research topic [29], [40]-[46].

While some of aspect-based sentiment extraction approaches apply rules of supervised learning, the others use rules of unsupervised learning. There are two main approaches for sentiment analysis [6] which are machine learning [47]-[49] and lexicon-based [50]- [52]. In the following subchapters, studies in the literature about supervised and unsupervised approaches are mentioned in more detail.

2.2.1 Machine Learning Approaches (Supervised)

The study performed by Gupta and Ekbal [53] proposed a combined system using different classifiers and Random Forest supervised machine learning algorithm to specify aspects and analyze sentiment classification of online reviews available for a popular product or service. As the results, the accuracies of 67.37% and 67.07% were obtained for the restaurant and laptops reviews, respectively. Mubarok, Adiwijaya, Aldhi [44] conducted aspect-based sentiment analysis approach to analyze and extract the polarity of sentiment from specific aspects of products reviews such as food, service, price, and ambiance. Naïve Bayes algorithm was used for the classification of sentiment polarity of aspects and evaluation resulting in an F1-Measure of 78.12%. Another study [54] was performed with aspect-based sentiment analysis method of different products in the marketing area. Aspects of product reviews were determined and each aspect was classified as positive, negative and neutral using SVM (support vector machine) and ME (Maximum Entropy) classification algorithms. In [55], the work described was about aspect-based sentiment analysis within laptop domains and restaurant domains. SVM was used to classify an aspect term into datasets using WEKA tool. The work resulted as accuracy of 70.5 % and 81.0 % for the laptop and restaurant domains, respectively. Kessler and Nicolov [56] conducted an aspect-based classification of product reviews using sentiment-target linking approach which ranked potential target mentions for a sentiment expression using SVM. Afzaal, Usman and Fong [57]

conducted an aspect-based sentiment framework to classify hotel and restaurant reviews using 5 machine learning techniques which are Naïve Bayes, SVM, ME, Random Forest Tree and FLR. They showed their evaluation results comparatively.

2.2.2 Lexicon Based Approaches (Unsupervised)

The success of machine learning does come with a significant price. Since a huge amount of preliminary processing as well as text-to-feature conversion are necessary, the analyses conducted with machine learning consume a significant amount of time to complete. Lexicon based approach has been popular for researchers because, this approach is easier to implement and is more understandable in opposition to machine learning because of less data required for successful analysis. The studies about this approach are divided into two subcategories which are called corpus-based and dictionary-based methods.

Dictionary-based approach often use sentiment lexicons, which include sentiment scores for each word, as a guide to specify which words or phrases are positive, negative or neutral in a generic context. In some studies, sentiment lexicons were constructed manually. A lexicon based method which was performed by Ding [50] was proposed to handle context dependent opinion words and distinguish multiple opinion words in the same sentence for aspect-based sentiment analysis of product reviews with 91% recall value.

In the literature, most studies used available sentiment dictionaries for English languages. Using WordNet [13] which is a basis sentiment dictionary for English languages, Kamps et al. [58] proposed a similarity measure to detect semantic orientation of adjectives. The evaluation was done against three factors of the General Inquirer [59] and highest value was 71.36%. Similarly, Hu and Liu [60] presented an article in which research was different from conventional work because they only mined aspects of the product which the customer gave his/her opinions. They specified these opinions as positive or negative using WordNet which enabled them to discriminate the semantic orientation of opinion words. This paper resulted with 84% average accuracy for the five products. Another study based on WordNet is presented by Albornoz et al. [61]. This study combined machine learning method

and dictionary-based method to analyze the polarity of online hotel reviews at aspect level. The evaluation results were an average accuracy of 71% with 3 categories and 46.9% with 5 categories. In 2015, Guha et al. [62] used WordNet while extracting features of online restaurant reviews. The study was completed into 3 slots: aspect category subtask, opinion target expression subtask and sentiment polarity subtask. WordNet was also used to classify sentiment of aspects combining different machine learning methods in the sentiment polarity subtask. In 2011, Khan et al. [63] proposed a rule-based approach for the semantic analysis of online customer reviews. Each word in the sentence was recorded using method "POS" and polarity of the given sentence in the review was computed. In this study, nouns were called "aspects" which were labeled as positive or negative using SentiWordNet [64] which was derived from WordNet. Accuracy was evaluated as 86%. Another study which was conducted using SentiWordNet was proposed by Singh et al. [65] which analyzed aspect level polarity of movie reviews. The obtained results were compared with Alchemy API [66] and showed that the accuracy of this study had higher value than the ones obtained with Alchemy API.

All studies mentioned above were conducted for the English language. There are also many studies using a sentiment dictionary which were performed for other languages. In the following, some examples of the research about agglutinative languages are explained, including the Turkish language. In 2012, Zhang et al. [27] proposed an aspect-based subjectivity analysis method to find product weaknesses and compare with other products in Chinese language. WordNet–Hownet [67] was used as a lexicon to analyze sentiment of aspects of products. The evaluation resulted with 85.26% as the general recall value. In Korean language, which is agglutinative, Han et al. [68] conducted a linguistic source for Korean languages. They constructed their dictionary with multiword aspects using frequency of terms. Another dictionary-based sentiment analysis approach was proposed in Arabic language by Ayyoub et al. [69]. They built their dictionary in 3 steps: gathering Arabic stems, translating them into English and taking an English sentiment lexicon to determine the polarity value of each word. Their evaluation result show that average accuracy value was 86.89%. In Turkish language, Turkmen, Ekinci and Omurca [29] determined the sentiment strength of hotel reviews for 10 aspects constructing the

sentiment lexicon manually. Another study which was published in 2015 was performed by Dehkharghan et al. [70]. This study proposed a complete framework for aspect-based sentiment analysis using three lexicons: SentiTurkNet, their own polar word list, and translation of the SenticNet [71]. The average accuracy values were for 73.42% for binary (positive, negative) and 60.33% for ternary (positive, negative and neutral). In 2016, Eryiğit [28] conducted aspect-based sentiment analysis of restaurant reviews on Twitter using TurkSent [72] as lexical source. After evaluation of the study, F1 score was obtained as 71%. In 2017, Kama et al. extracted implicit and explicit aspects from online Turkish product reviews and matched them semantic polarity values .In 2019, Kama et al. [73] developed an online application to analyze aspect-based sentiment analysis of online Turkish phone reviews. Frequency based aspect extraction method was used in this study, which was explained detail in 2016 [74]. Then, aspect–sentiment matching was done using a Turkish sentiment dictionary.

2.3 Natural Language Processing

Natural Language Processing (NLP), is a branch of artificial intelligence that deals with the interaction between computers and humans using natural language. The ultimate objective of NLP is to read, decipher, understand, and make sense of human languages. NLP can be considered as a combination of different tasks such as grammar induction, lemmatization, segmentation, stemming, morphological segmentation, part of speech tagging, parsing and tokenization.

In recent years, fields of application of NLP have increased on a daily basis. NLP can be segmented into two parts as text processing and speech processing in terms of the given input. For example, in terms of text processing, a researcher at IBM [75] developed a cognitive assistant that works as a personalized search engine by learning all about the user and then reminds the user of a name, a song, or anything when he/she needs it. Another example of text processing is The NLP Group at MIT [76] conducted a new system to identify fake news. As for of speech processing, Amazon’s Alexa and Apple’s Siri [77] are examples of intelligent voice driven interfaces that use NLP to respond to vocal prompts and perform various tasks such as find a particular shop, tell the weather forecast, suggest the best route to the office or

turn on the lights at home. Another popular application by researchers and also useful application of NLP is developed with the aim of analyzing sentiments of customers about a service or product by identifying and extracting information from diverse sources in many languages (Figure 2.1).

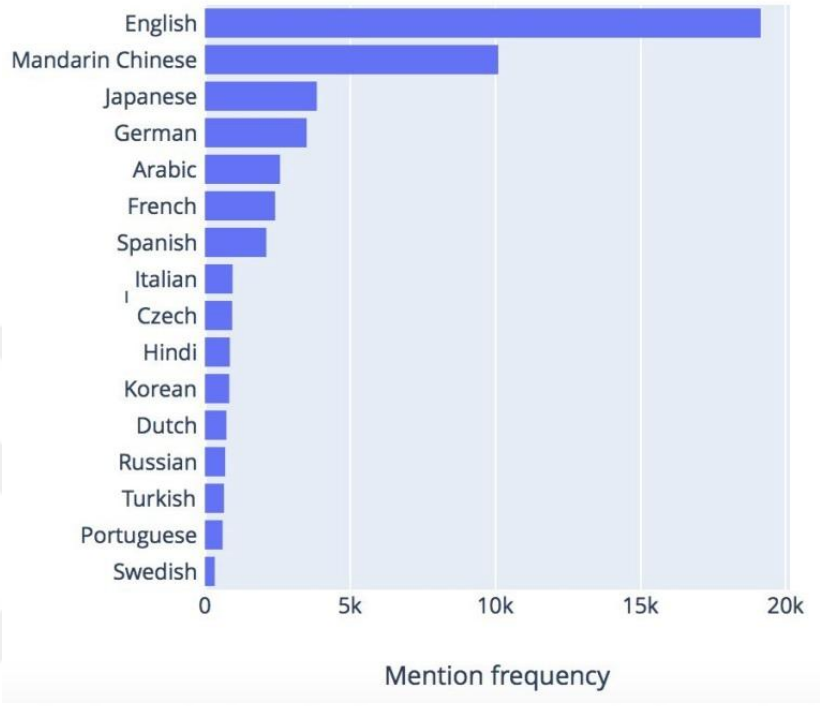

Figure 2.1 Languages addressed by ACL research [78]

As can be seen in Figure 2.1, most of applications of NLP were developed for the English language. Hu and Liu [60] proposed an aspect-based sentiment mining and summarizing method in which NL-Processor [79] was used to split sentences into words and to generate the label (noun, verb or adjective) for each word for POS tagging. Maipradit et al. [80] used spaCy library [81] as the NLP tool performing NLP tasks which were removing stop words, removing special characters, tokenization and tagging part of speech on three datasets which were taken from Stack Overflow, reviews of mobile applications, and Jira issue trackers. Ghiassi et al. [82] conducted standard NLP tasks transforming the text into a vector representation which is called the bag-of-words, manually. In the term weighting task of NLP, term-frequency/inverse document frequency (TF/IDF) algorithm was used. Jawala et al. [12] developed an opinion discovery system for feature based sentiment analysis of mobile phone reviews. The Natural Language Toolkit [83] which is the set of Python

based libraries was used for performing of NLP tasks in the their system. Another NLP tool which is called Stanford POS tagger [84] was used in aspect-based sentiment analysis method developed by Kansal and Toshniwal [85].

Although most of studies of NLP were proposed for the English language, there are a remarkable number of studies proposed for the Chinese language (Figure 2.1). Chinese language has no text delimited by spaces. Therefore, segmentation task is needed to perform in the application of NLP which was conducted in Chinese language. Zhang et al. [27] conducted a system to find negative aspects of products from online product reviews. They applied segmentation in addition to the standard NLP tasks, which were removing duplicate reviews, converting traditional to simplified, POS tagging, removing stop words and misspelling correction, by using ICTCLAS [86].

According to Figure 2.1, there are limited research about NLP for the Turkish language which is a difficult language to work with. Turkish is a morphologically rich language. It is an agglutinative language and multiple suffixes can inflect a stem. Every new suffix addition may transform the meaning of the word or its syntactic role in the sentence. The word “korkusuzca” is given as an example which means “fearlessly” in English. The stem of the word is “korkmak“ which is a verb. The Suffix “-u” makes the word a noun. Then the suffix “-suz” changes the meaning to opposite. The last suffix “-ca” makes noun an adverb. As can be seen with the example, correct implementation of the tasks of NLP such as stemming, POS tagging, morphological segmentation and lemmatization are crucially important for the Turkish language. In this context, Dehkharghani et al. [70] proposed a sentiment analysis system of Turkish movie reviews at different levels: aspect, word, sentence and document. They used ITU Turkish Parser [87] as the NLP tool which takes a sentence as input and creates a dependency tree with morphological analysis for each word in the sentence. Yıldırım et al. [88] conducted a sentiment analysis method of Turkish tweets about telecommunication products. They carried out NLP tasks which were normalization, stemming and negation handling using hand-annotated sentiment corpus. Vural at al. [19] proposed a framework to detect sentiment polarity of Turkish hotel reviews. They performed morphological analysis using Zemberek

[18] which is an open source natural language processing library. Morphological analyzer function of Zemberek takes a word as an input and gives as output all possible roots and suffixes of the input. Omurca, Ekinci and Turkmen [89] proposed a system to detect multi-word aspects of Turkish Hotel Reviews. They used Zemberek [18] to parse reviews and tag each word as noun, verb, adjectives or etc. in the reviews. Omurca, Ekinci and Turkmen [29] also used Zemberek Library to perform stemming and POS tagging in their aspect-based sentiment analysis of Hotel reviews system. Ekinci and Omurca [90] also used Zemberek Library [18] for conducting a LDA based system to extract aspect-sentiment pair. Uysal et al. [91] performed an aspect-based sentiment analysis before the Turkish general election in 2015. They collected tweets about Turkish parties which are assumed as aspects in this study and applied two NLP tasks which are misspelling correction and stemming using Zemberek Library [18].

CHAPTER 3
DESIGN AND IMPLEMENTATION

3.1 Design

The architectural overview of our system for aspect-based sentiment analysis of online iPhone™ review is illustrated in Figure 3.1. All of the processes are divided into four subtasks. In order to evaluate the aspect-based sentiment analysis of online iPhone™ reviews, our system needs to gather the review data from web. However, the raw data may contain duplicated comments and misspelled words as well as punctuation and stop words which are meaningless. Therefore, preprocessing is needed to be done before sentiment analysis. As it is seen in the example from Figure 3.2, different feature words can refer to one aspect, such as the words “lens”, “video”, “fotoğraf” and “çekim” all referring to the aspect “kamera”. So, extracting and grouping the features into different aspects are very important to find whether a sentence includes an aspect. Aspects can be referred by explicit and implicit features. An explicit feature implies to the aspect directly in a sentence, while an implicit feature implies the aspect indirectly. The reviews which are obtained from the web are examined, and the words found with the most frequency were labeled as explicit features and implicit features. Then, an aspect-based sentiment analysis module was developed to determine the sentiment polarity of each aspect. The details of these subtasks are introduced and explained in the following subsections.

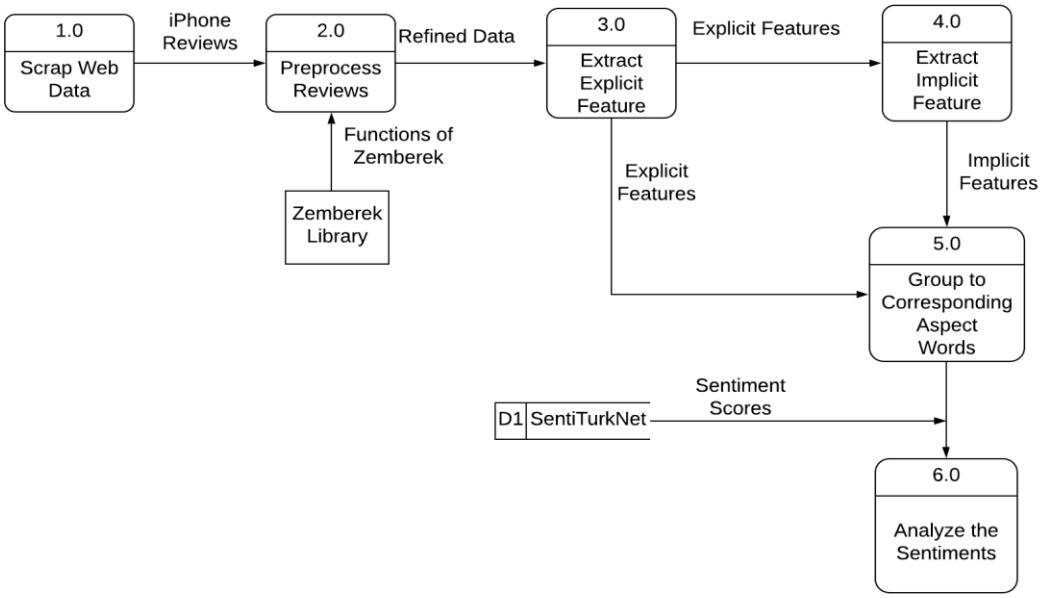

Figure 3.1 The architectural overview of our system

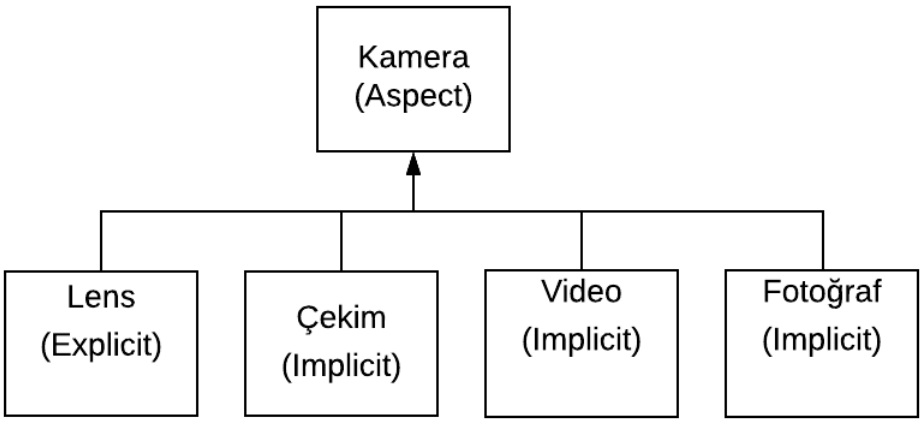

Figure 3.2 The relationship between an aspect and its explicit and implicit features

3.1.1 Data Gathering

The data were collected from two websites, Hepsiburada and EkşiSözlük, both of which are vast data sources in terms of product reviews in the Turkish language. The first one is one of most popular e-commerce website in Turkey. On December 2019, 69.5 million people visited Hepsiburada and 98.07% of the visitors live in Turkey [92]. The second website, on the other hand, is a dictionary-like website composed of comments about a variety of topics posted by users which is considered as one of the

largest communities in Turkey. According to SimilarWeb, more than 108.57 million people visited EkşiSözlük on December 2019 and 91.79% of those were from Turkey [93].

The method used for data gathering is web scraping. Web scraping can be done with an automated tool using HTTP or manually from a web browser using HTML [94]. In this study, a semi -manual approach was conducted using Python. In order to get the data required from web pages, the following steps were done. First, a table which is a part of the HTML code of the website was taken using the URL given in Appendix A which was then passed to the Beautiful Soap. The Beautiful Soap is a Python library used as an HTML parser. It creates a parse tree which enables data extraction from HTML. HTML is a standard markup language for a document designed to be displayed in a web browser. HTML facilities can be enhanced using Cascading Style Sheets (CSS) and scripting languages. The architecture of the HTML tags is commonly similar in most webpages. In this thesis, the tags which start with “class=review-text” within “p” were extracted from the HTML table. In Table 3.1, the meanings of the HTML tags that were used in scraping were explained. Finally, these tags were converted to plain text and copied to a spreadsheet. By using this procedure, a total of 5483 reviews were collected in the end.

Table 3.1 Meaning of HTML elements [95]

<p>	Paragraphs are defined with the <p> tag.
class	It is used to define equal styles for elements with the same class name.
Attribute	Attributes provide additional information about an element.

3.1.2 Data Preprocessing

Before the extraction of the implicit and the explicit features, the raw data that was collected from the websites preprocessed. The preprocessing steps in this study are illustrated in Figure 3.3.

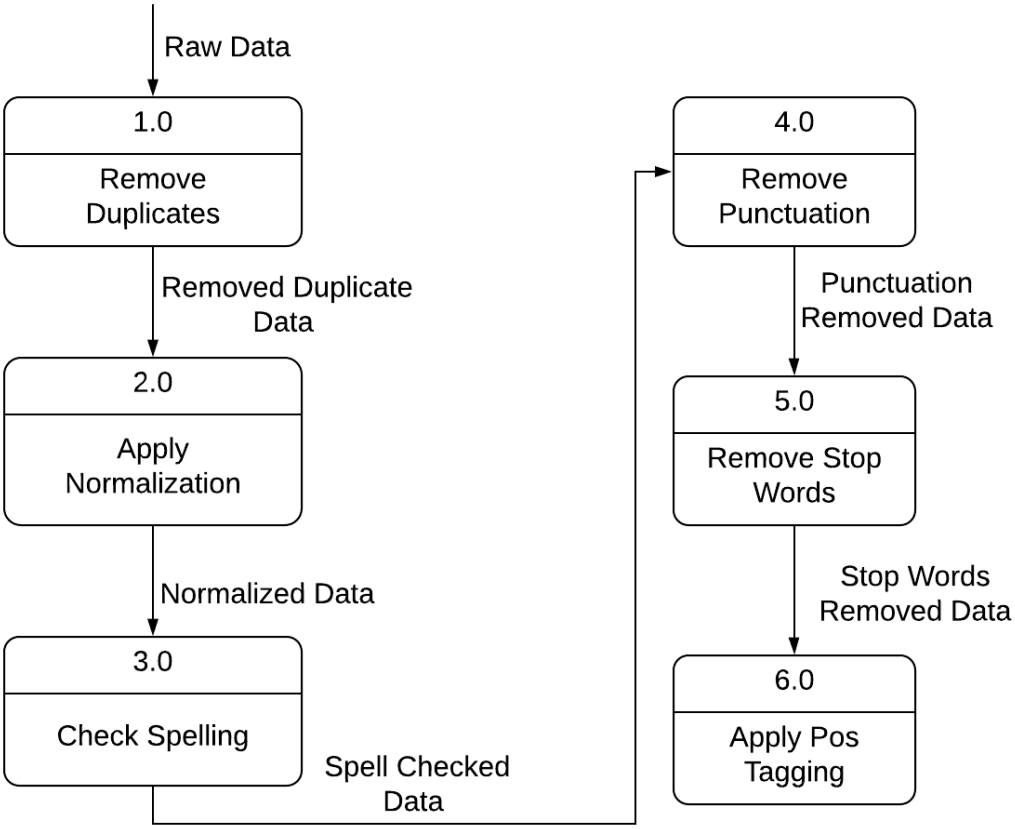

Figure 3.3 The preprocessing tasks of the system.

Customers may sometimes send the same comment more than once as a result of websites not responding quickly which creates duplicate reviews. This causes incorrect results for sentiment analysis. Therefore, these duplicate reviews were removed resulting in 5430 reviews in the end. The users may also submit their comments with mistypes or informal speech which must be corrected to increase the success of the processes applied to the data in the later steps. For this purpose, the normalization function of Zemberek was used. Zemberek is a Turkish NLP library which is flexible, open source and platform independent framework. It mainly enables obtaining language structure information and applying basic NLP operations such as normalization, spell checking, morphological parsing and converting the words written only using ASCII characters. It makes preprocessing Turkish texts easier for developers [18]. In this thesis, the missing characters were added, and all characters were converted to lower case via normalization operation of Zemberek which is the type of operation that corrects user mistakes in review texts. However,

correctness of text is still not guaranteed yet. Therefore, in order to increase the success of the aspect-based sentiment analysis, spell checking operation was used. In the spell checking operation of Zemberek, function returns a suggestion list for a word given as input. The first word in the list is always more accurate. Therefore, in this study, the first word was always picked and replaced with the input. The punctuations and the stop words, on the other hand, are meaningless in terms of aspect-based sentiment analysis. So, with the following data preprocessing steps, punctuations and stop words (Appendix D) were removed to decrease the memory load of the program. An example for the preprocessing steps mentioned so far can be seen for a single review in Table 3.2.

Table 3.2 Examples of preprocessing steps of the review.

NLP Operations	**Customer Review**
Raw	Sahip oldugum iphone telefona guncelleme geldi ve bir ay byunca sim kart gormedi. Sonra duzeldi. Bu sirada mecburen yeni telefon aldim. Tesekkurler iphone.
Normalized	sahip olduğum ıphone telefona güncelleme geldi ve bir ay boyunca sim kart görmedi . sonra düzeldi . bu sırada mecburen yeni telefon aldım . teşekkürler ıphone .
Spell Checked	sahip olduğum phone telefona güncelleme geldi ve bir ay boyunca sim kart görmedi . sonra düzeldi . bu sırada mecburen yeni telefon aldım . teşekkürler phone .
Punctuation Removed	sahip olduğum phone telefona güncelleme geldi ve bir ay boyunca sim kart görmedi sonra düzeldi bu sırada mecburen yeni telefon aldım teşekkürler phone
Stop Words Removed	sahip olduğum phone telefona güncelleme geldi ay boyunca sim kart görmedi düzeldi sırada mecburen yeni telefon aldım teşekkürler phone

The final step of data preprocessing is POS Tagging. The morphology function of Zemberek enables getting language structure information as output. Turkish is an agglutinative language. Therefore, polarity of the roots and the suffixes are very important in terms of aspect-based sentiment analysis in Turkish. Morphology function takes a word and returns the root and polarity of suffix of the word. In Table 3.3, the first column is the preprocessed customer review; second column is the

morphological analysis of the word “görmedi”. It is seen from the result of the morphological analysis that “-me” is negative suffix. “-me” is the negation particle in Turkish which changes the word to negative. Hence, the resulting polarity is interpreted as negative for “görmedi”.

Table 3.3 Example of output belong to morphology function.

Preprocessed Review	**Output of morphological analysis of “Görmedi”**
“sahip olduğum phone telefona güncelleme geldi ay boyunca sim kart görmedi düzeldi sırada mecburen yeni telefon aldım teşekkürler phone”	[görmek:Verb] gör:Verb+me:Neg+di:Past+A3sg

3.1.3 Feature Extraction and Grouping

Feature extraction and grouping to aspects are crucial in terms of the success of aspect-based sentiment analysis. We have examined all of the reviews and determine the following three words as aspects which we think have the most frequency: “kamera”, “performans” and “fiyat”. Also, there are some words which refer to these aspects explicitly or implicitly. The explicit features in the same group are usually the synonyms or the similar concept words. Accordingly, we have determined the explicit features concerning the iPhone domain. The implicit features usually have the same or close meaning to aspects and explicit features. In Table 3.4, all aspects and features of specified in our system are presented.

Table 3.4 All Aspects and features extracted in our system.

Aspect	**Explicit Feature**	**Implicit Feature**	**Implicit Feature**	**Implicit Feature**	**Implicit Feature**
Kamera	Lens	Foto	Fotoğraf	Çekim	Video
Performans	Hız	Batarya	Şarj	Ekran	Güncelleme
Fiyat	Ücret	Pahalı	Ucuz	Para	

3.1.4 Aspect-Based Sentiment Analysis

Sentiment analysis is important for our study because it specifies whether the customer is satisfied with a specific aspect of the product or not. Our dataset is in a single domain and some reviews consist of a few sentences, so we apply an easy but effective sentence-level and lexicon-based sentiment analysis to identify the orientation of each sentence. Our sentence-level analysis consists of two main parts: word-level and word-group level. While morphological analysis function is applied, some questions are answered and saved as an object for each word within the all data. The questions are "What is root?", "Is root a feature?", "What is the suffix?", "Is the suffix negative?". After these steps are performed for all of the reviews, the polarity of each root is searched at SentiTurkNet [20] which is a Turkish polarity lexicon developed for sentiment analysis. SentiTurkNet is an extended work of WordNet [13]. Three polarity values are assigned to each word placed at Turkish WordNet, specified as positive, negative and objective (Figure 3.4). In this study, only positive and negative polarity values of SentiTurkNet are used and neutral polarity value is ignored. If the difference between positive and negative values is greater than zero, the root of the word is accepted as positive, otherwise it is accepted as negative. For example, root and suffix of the word "Güzeldir" is taken as"Güzel" and "-dir" after morphological analysis. "Güzel" is found in SentiTurkNet and the difference value is "1" which is considered to be a positive root in our study. Additionally, we know, from output of morphological analysis function by Zemberek, that the suffix "-dir" is also positive. So a positive root with a positive suffix is evaluated as a positive word as in the word "Güzeldir". As can be seen in Table 3.5, if both the root and the suffix are either positive or negative, the word is evaluated as positive, and if one of them is positive or negative while the other one is the opposite, the word is then evaluated as negative.

	A	B	C	D	E	F	G
1	synonyms	Turkish Gloss	Polarity Label	POS tag	neg value	obj value	pos value
9	1 Nisan	nisan ayın birinci günü	o	n	0,06	0,872	0,068
10	aba	Yünden, dövülerek yapılan kalın ve kaba kumaş	o	n	0,06	0,872	0,068
11	abanmak	Bir yere veya bir kimseye yaslanmak, dayanmak	o	v	0,06	0,872	0,068
12	abanoz	Abanozgillerin ağır, sert ve siyah renkli tahtası	o	n	0,06	0,872	0,068
13	abanoz	Abanozgillerin ağır, sert ve siyah renkli tahtası	o	n	0,06	0,872	0,068
14	abartı , mübalağa	oldugundan daha onemli gostermek	o	n	0,06	0,872	0,068
15	abartılı	represented as greater than is true or reasonable	n	a	0,47	0,462	0,068
16	abartmak , mübalağa etmek	Bir şeyi olduğundan büyük veya çok göstererek anlatmak, mübalâğa etmek	n	v	0,909	0,091	0
17	abdest , aptes	Müslümanların, bazı ibadetleri yapabilmek için el, ağız, burun, yüz, kol ve ayağı yıkama ve başa, enseye ıslak el gezdirme, kulağı temizleme biçiminde yaptıkları arınma.	p	n	0,06	0,06	0,88
18	Aberdeen	Aberdeen, İskoçya'da bir sehir statusu bulunan kent. Kuzeydoğu İskoçya'nın en önemli limanı ve ticaret merkezi olan Aberdeen, Kuzey Denizi kıyısında yer alır. Edinburg'dan 94 ve Londra'dan 649km uzaktadir.	o	n	0,06	0,872	0,068
19	Abican	Fildişi Sahilleri`nin en büyük şehri	o	n	0,06	0,872	0,068
20	Abies genusu , Abies cinsi	Köknar olarak bilinen iğne yapraklı ağaç cinsi	o	n	0,06	0,872	0,068
21	abla	Bir kimsenin kendinden büyük olan kız kardeşi.	o	n	0,06	0,872	0,068

Figure 3.4 SentiTurkNet

Table 3.5 Combination of root and suffix in Turkish.

Word / Word Group	Negative Value of Root	Pos Value of Root	Root	Suffix	Evaulated Value
Güzeldir	0	1	Güzel (1, positive)	-dir (positive)	Positive
Zahmetsiz	0,068	0,06	Zahmet (-0,008, Negative)	-siz (negative)	Positive
Sorunlu	0,068	0,06	Sorun (-0,008, Negative)	-lu (positive)	Negative
Tanımadı	0,06	0,068	Tanımak (0,008, Positive)	-ma (negative)	Negative

3.2 Implementation

In this section of the thesis, implementation of our aspect-based sentiment analysis system is explained in detail. Implementation chapter is arranged into two main parts. The first part is named as “Data Analysis” which presents the implementation of the following steps: data gathering, data preprocessing, incorporating aspects and

features into the system and analyzing the root and suffix of the word. The second part, “Aspect-Based Sentiment Analysis”, explains the implementation of word-level and word-group level sentiment analysis along with their algorithms. Data gathering part was written in the Python language by Spyder [96] which is an IDE. The rest of the system was written in the Java language by IntelliJ IDEA [97] which is also an IDE. In addition to this, what types of challenges were faced and how these challenges were handled are also explained in the following sections.

3.2.1 Data Analysis

In this thesis, customer reviews about iPhone are collected from two websites which are Hepsiburada and eksisozluk via web scraping method that is explained in detail in section “3.1.1”. The challenge was Turkish characters while data scraping. Because The Beautiful Soap library of Python [98], which was used for web scraping, does not accept Turkish characters. So, characters were converted with UTF-8. The total number of reviews collected was 5483. 5430 reviews remained after removing the duplicates

In this thesis, data preprocessing step was very important to increase the success of aspect-based sentiment analysis. This step prepares the reviews for sentiment analysis. For this purpose, some NLP operations were applied to the reviews which are normalization, spell checking, removing punctuation and stop words. Normalization operation of Zemberek library is needed to correct mistypes. Each review is sent to the normalize function of Zemberek, which returns the review by adding the missing characters and changing all characters to lowercase. In order to support the normalization operation, spell checking operation of Zemberek output of the normalization function is sent to the spellChecking function. Also, removing punctuation and stop words are applied to each review in turn since punctuations and stop words are meaningless for this thesis. RemovePunctuation function was taken the review which was output of spellCheck function (Appendix B). Examples of all of these processes can be seen in Figure 3.5.

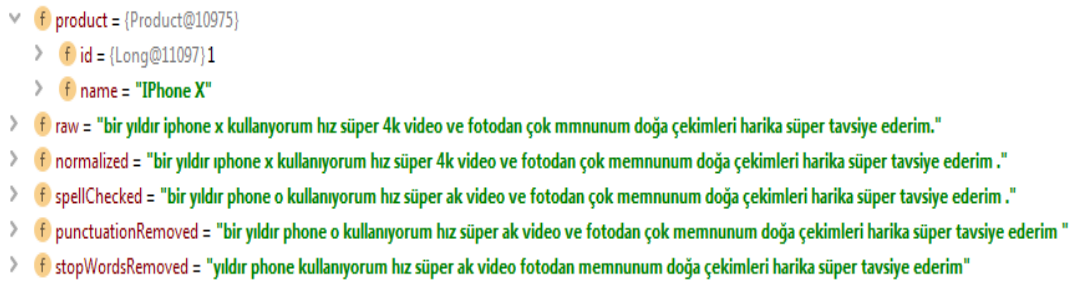

Figure 3.5 Example of preprocessed review

In order to incorporate aspects and features, which are explained in detail in section 3.1.3 into the system, a graphical user interface was implemented (Figure 3.6).

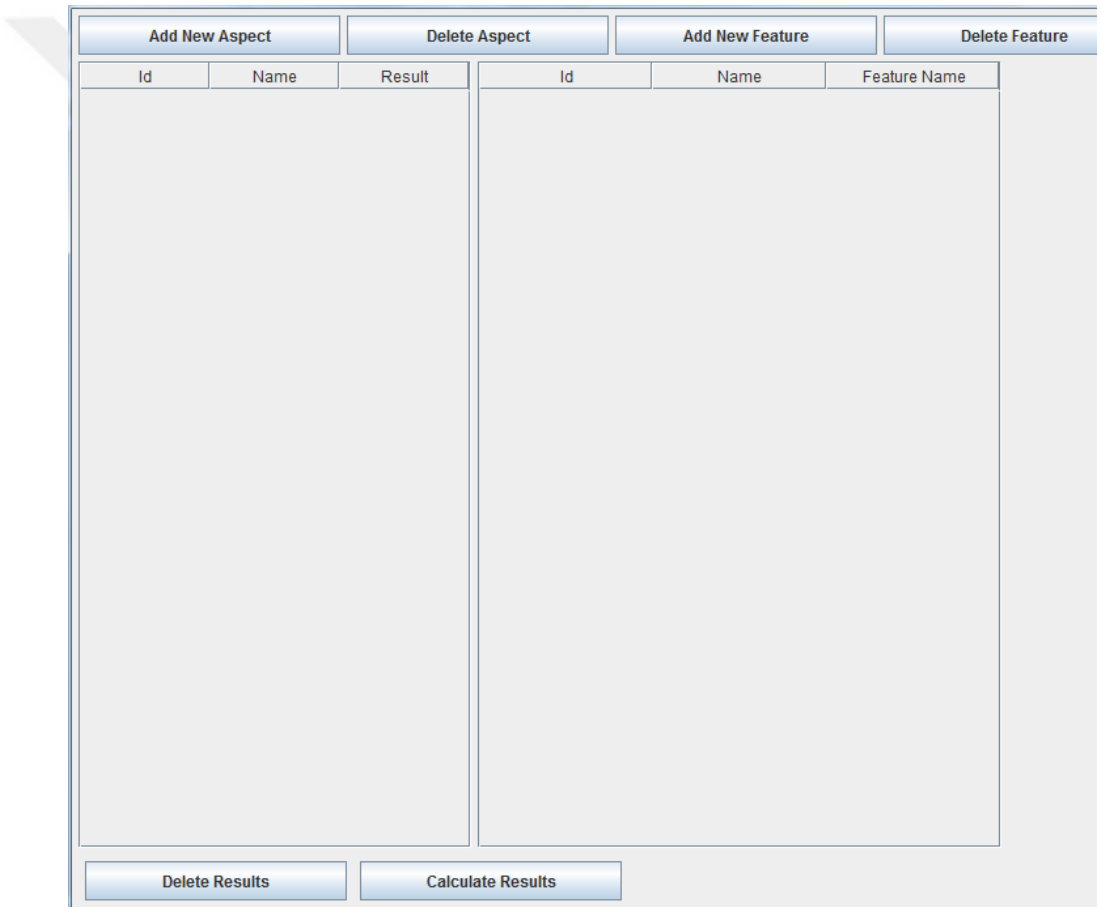

Figure 3.6 The GUI to manage of aspects and features

The user interface includes two parts. First part enables the user to enter the aspects specified by using “Add New Aspect” button (Figure 3.7).

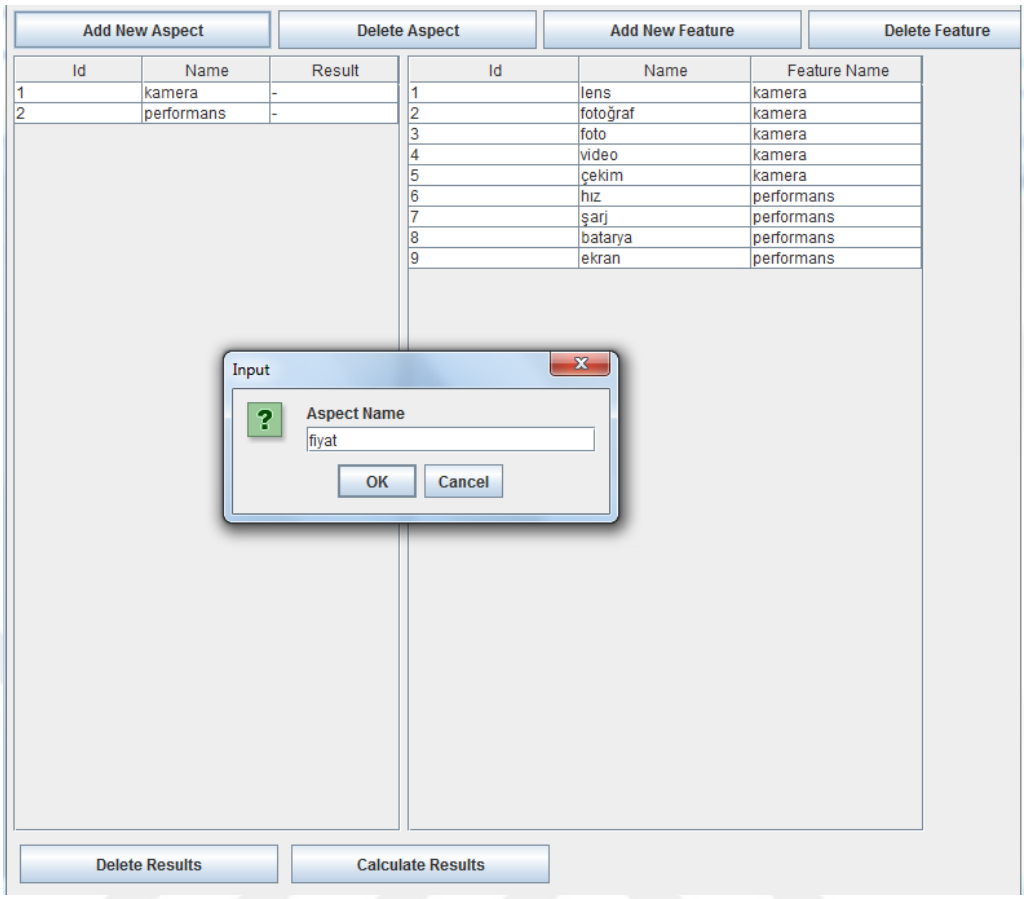

Figure 3.7 Adding an aspect to the system

Second part enables the user to enter features which refer to corresponding aspects by using “Add New Feature” (Figure 3.8).

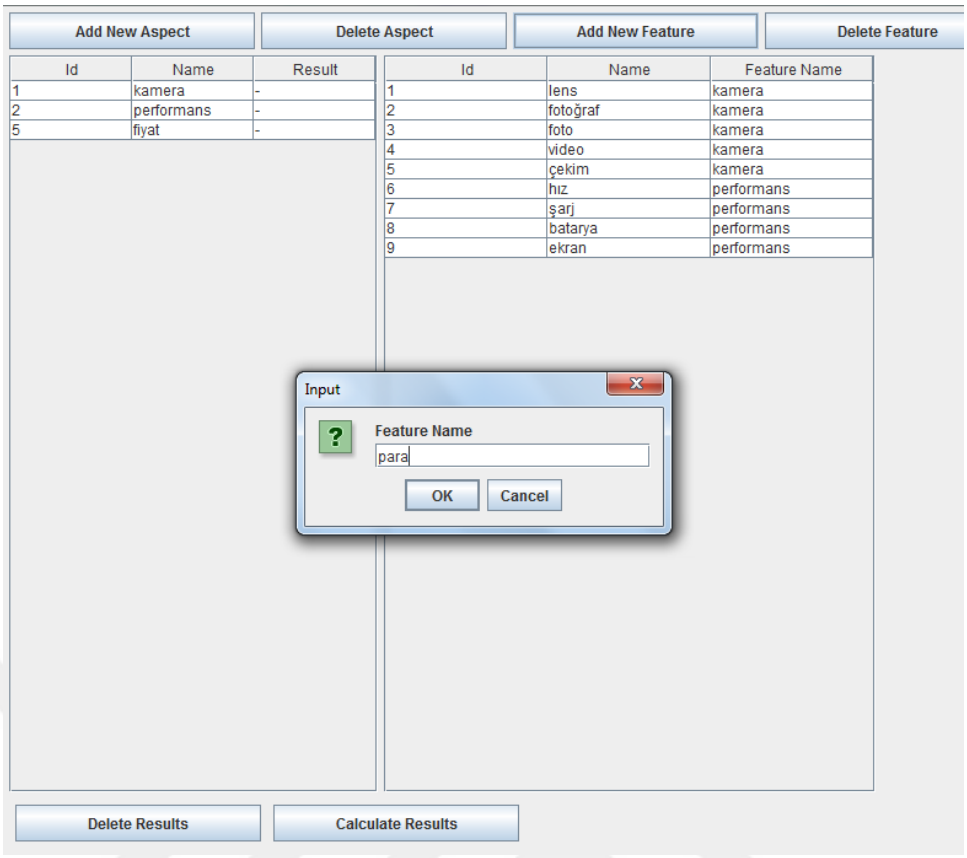

Figure 3.8 Adding feature to the system

After the feature name is entered, a window is opened to enter corresponding aspect name (Figure 3.9). All aspects and features can be deleted using “Delete Aspect” and “Delete Feature” buttons. However, if an aspect needs to be deleted, the corresponding feature must also be deleted. In this study, the challenge was the incorporation of the “ücret” word to the system as features. “Ücret” feature refers to “fiyat” aspect because they have close meaning. However, when “ücret” feature was incorporated to the system, the system analyzed as if “asgari ücret” was an “ücret” feature. The reviews including “asgari ücret” were unrelated to the price of iPhone. All aspects and features extracted must be related with iPhone. Therefore, “ücret” feature was removed from Table 3.4 as mentioned in Section 3.1.3.

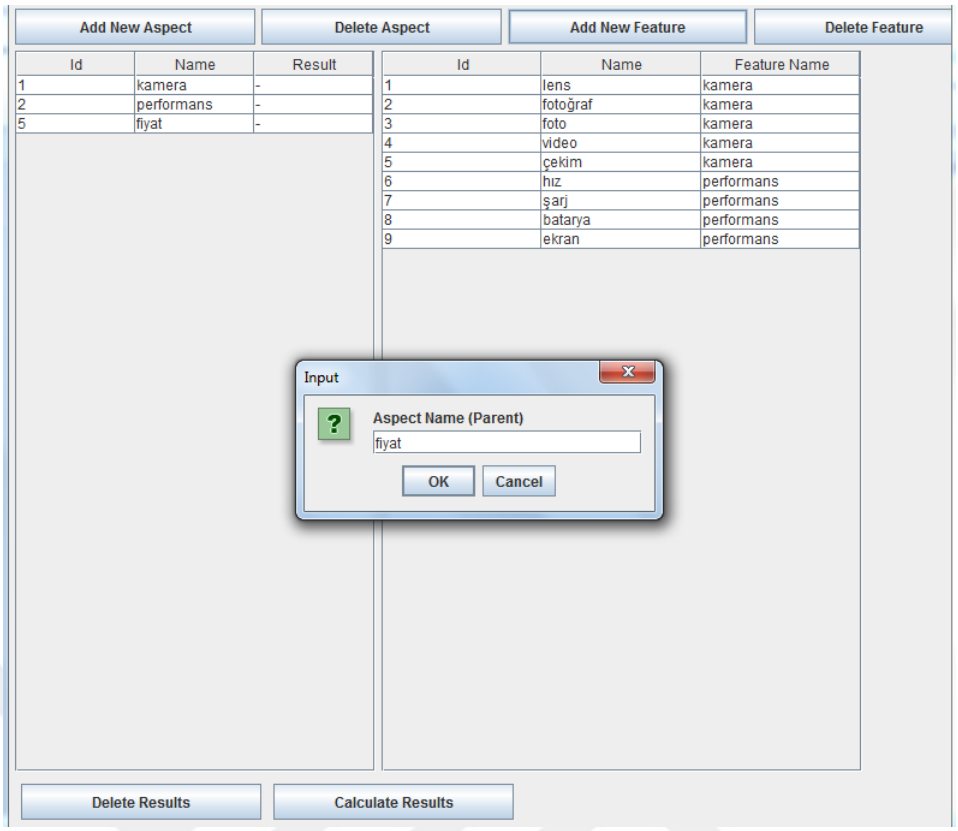

Figure 3.9 Adding parent aspect to the system

When all aspects and their features are entered to the system, the GUI is seen as in Figure 3.10. Calculating semantic analysis result for each feature and its corresponding aspect starts when “Calculate Results” is clicked.

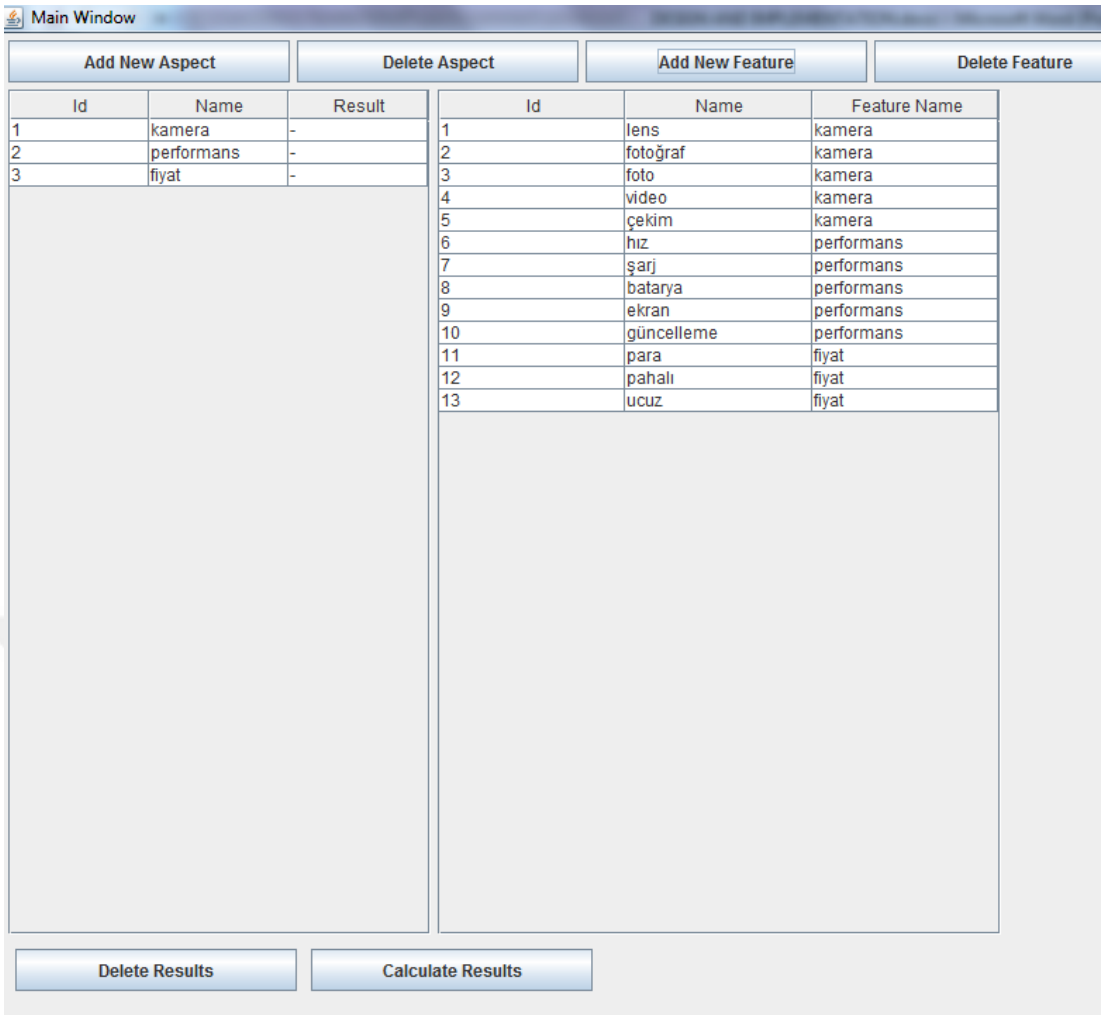

Figure 3.10 The appearance after all aspects and features added

In order to calculate the semantic analysis result for each feature and its corresponding aspect, root and suffix of the word were analyzed initially. As can be seen in Appendix C, each review was taken by removing the stop words. An example output of this process can be seen in Figure 3.11.

```
phone ürünlerin ekran sorunu kesinlikle tavsiye etmiyorum kullanıyorum garantiden telefonum gelmiyor
türlü 1 hafta içinde 2 ekran değişti toplam 3 ekran değişti sürü sorunu telefonumu batarya
sağlamlığı 95 hmemn hemen yıllık telefon olmasına
```

Figure 3.11 The example of removing stop words

Then, output is passed to the analyze sentence function of the morphology object in the Zemberek library. Analyze sentence function returns a detailed analysis of the

word. The output of analyze sentence function which was given the input "etmiyorum" can be seen in Figure 3.12.

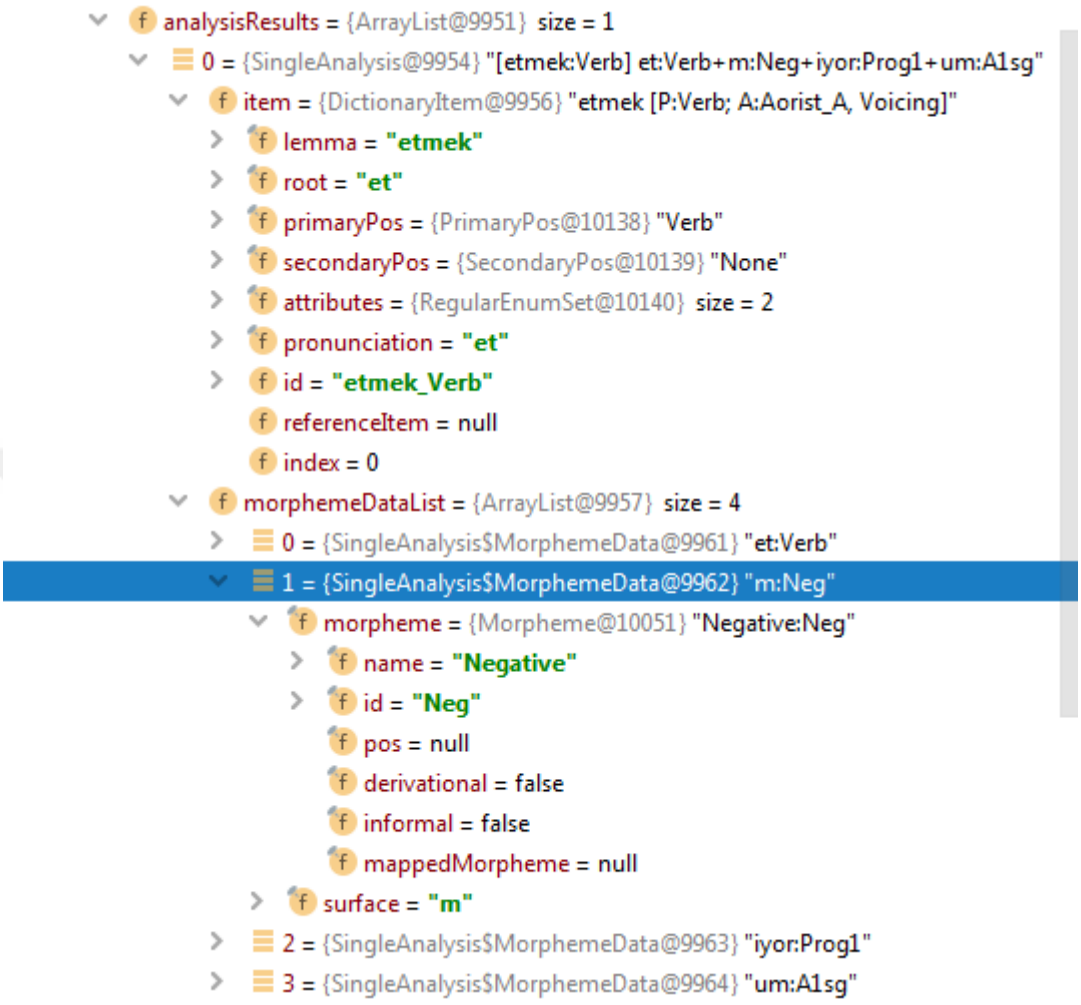

Figure 3.12 The example of POS Tagging

The wordAnalysisResults object is created and the following variables are set into this object applying the rules in Algorithm 3.1.

Algorithm 3.1 Data Root and Suffix Analysis Algorithm

Where:
-C: each comment in reviews
-W: each word in reviews
-R: root of the word
-S: suffix

```
-N:      Is suffix negative?
-F:      Is root feature?
-A:      aspect refer to feature
-FT:     feature word
-FL:     feature list
-Obj:    result Object
-M(w):   analyzeSentence function of Zemberek library

1:  for each word W in sentence C do
2:      pass word to M(W)
3:      set W into Obj
4:      set R into Obj
5:      if R into FL
6:          set F as True into Obj
7:          set FT into Obj
8:          set A into Obj
9:      end if
10:     if N is negative suffix
11:         set N as True into Obj
12:     end if
13:     return Obj
14: end for
```

The variables which are set into the object are the ”etmiyorum” word, root of word as “et”, Boolean value of the suffix being negative as “True”, Boolean value about word being a feature or aspect as “False”. The output of wordAnalysisResults object for the “etmiyorum” word can be seen in Figure 3.13. Also, the words placed in Figure 3.11, “ekran” is set as feature and not negative, “tavsiye” is set as not a feature and not negative (Figure 3.13).

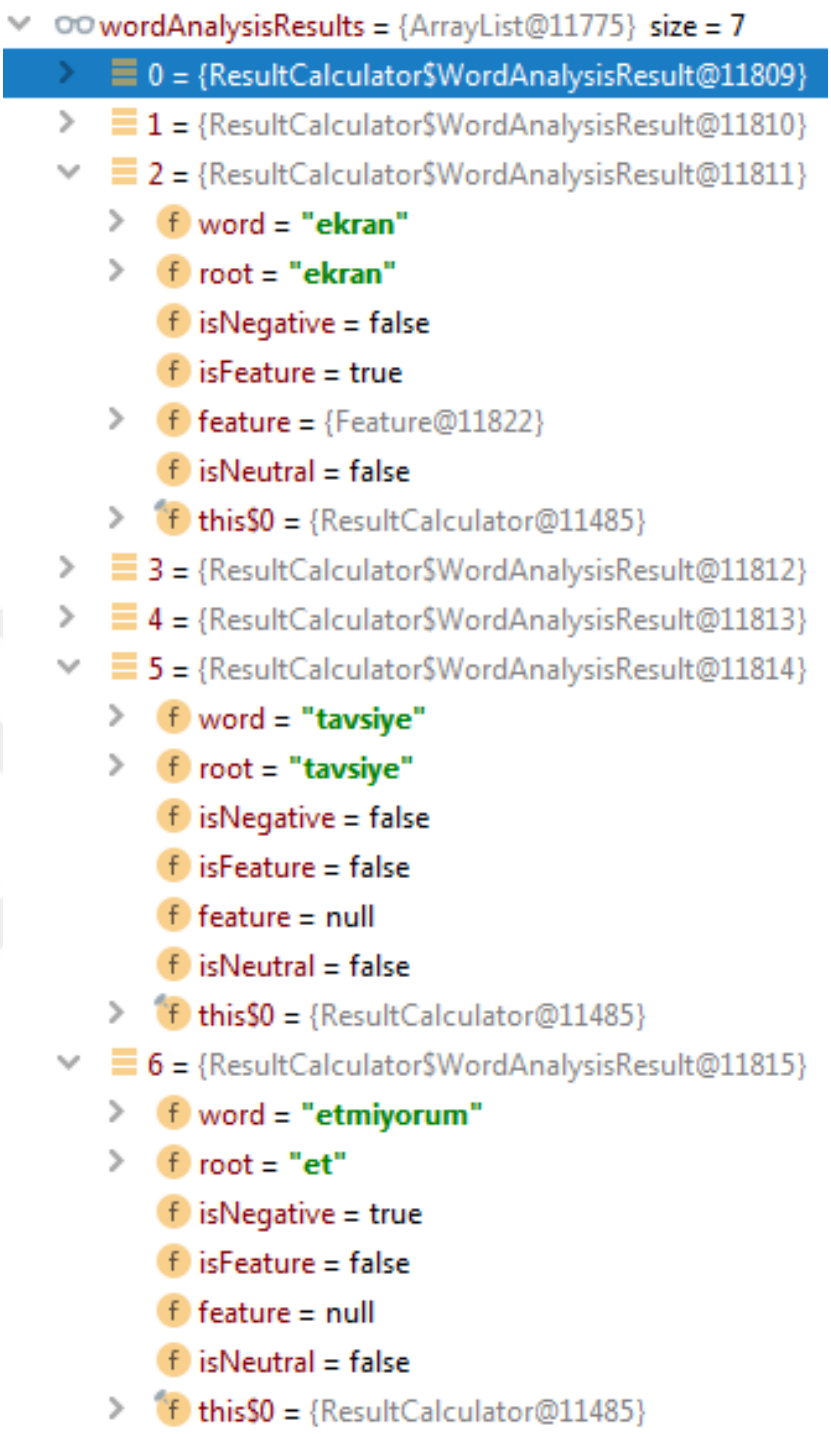

Figure 3.13 The example of word analysis result

3.2.2 Aspect-Based Sentiment Analysis

The aim of this thesis is developing an aspect-based sentiment analysis system for reviews on iPhones given in the Turkish language. All of processes which were explained in Section 3.2, were developed for this aim. Firstly, data were analyzed as root and suffix, and then features were extracted grouped into corresponding aspects.

In this part, the final processes are explained to find the polarity of the root in SentiTurkNet [20] and to assign the polarity corresponding to the aspect in two levels which are world-level and word-group level.

3.2.2.1 Word Level Aspect-Based Sentiment Analysis

In this study, word-level aspect-based sentiment analysis is implemented by applying the rules illustrated in Algorithm 3.2.

Algorithm 3.2 Word Level Analysis Algorithm

Where:
-R: each review in the data set
-C: each comment in reviews
-W: each word in reviews
-R: Root of the word
-N: Is suffix negative?
-F: Is root feature?
-FT: Feature word
-A: Aspect refer to feature
-PF: Previous feature in the comment
-S: SentiTurkNet
-P: Positive value of word in the SentiTurkNet
-N: Negative value of word in the SentiTurkNet
-PW: polarity of word
-AP: polarity of aspect
-R: Result polarity value

```
1:  for each C in review R
2:      for each W in comment C
3:          Set AP = 0 and PF = null
4:          if the F is True
5:              if PF is not null
6:                  set A as PF
7:                  set AP as PW
```

```
8:              else set PF as F
9:              end if
10:         else search root into S
11:             if S is not null
12:                 Set PW as P – N
13:                 if PF is "fiyat" and root is "yüksek"
14:                     Set AP += -PW
15:                 else if PF is "fiyat" and root is "düşük"
16:                     Set AP += -PW
17:                 else if PF is not"fiyat" and N is True
18:                     Set AP += -PW
19:             else set AP += PW
20:             end if
21:         end if
22:     end for
23:     for each A into comment
24:         Set  AP and corresponding A
25:     end for
26: end for
```

As can be seen in Appendix C, the following activities are performed for each word. For instance, a comment can be comprised of more than one feature or aspect. Therefore, the transition of aspects must be clarified in the comment with the aim of assigning the polarity of words to the right aspect. So, a variable called previousAspect that will contain the specific aspect to be analyzed in the comment is created and set to null initially. Then, to contain the polarity value of the aspect analyzed, another variable called aspectValue is created and set to zero as initial value. Finally, an object containing both variables is created, and the aspect that is analyzed as well as its polarity value based on the polarity of each word related to the aspect will be set into the object. If the word is an aspect or a feature related to an aspect and previousAspect is not null, the word is set as previousAspect and polarity of the word is set as aspectValue is assigned to zero again (in Algorithm 3.2). If the word is not the aspect or the corresponding feature, the root of word, which is extracted from wordAnalysisResults object as explained in Section 3.2.1 in detail, is

searched in SentiTurkNet [20]. SentiTurkNet has three columns about the polarity values of words which are negative, objective and positive (Figure 3.4). If the root of word is found in SentiTurkNet, the value difference of positive and negative columns is obtained and set as featureValue as long as the suffix is not negative. However, if it is negative, the difference value is multiplied with negative sign before being set as featureValue (line 7 - 14, in Algorithm 3.2) since, Turkish language has negation suffixes such as "-me", "-ma", "-sız", "-siz". As can be seen in Figure 3.14, the suffix "-mi", which was deviated from "-me" by changing vowel from high to low [99], converted the positive root "et-" to negative. Therefore, the difference polarity value "0.01" which is obtained from SentiTurkNet was multiplied by "-1" and then assigned to the corresponding aspect.

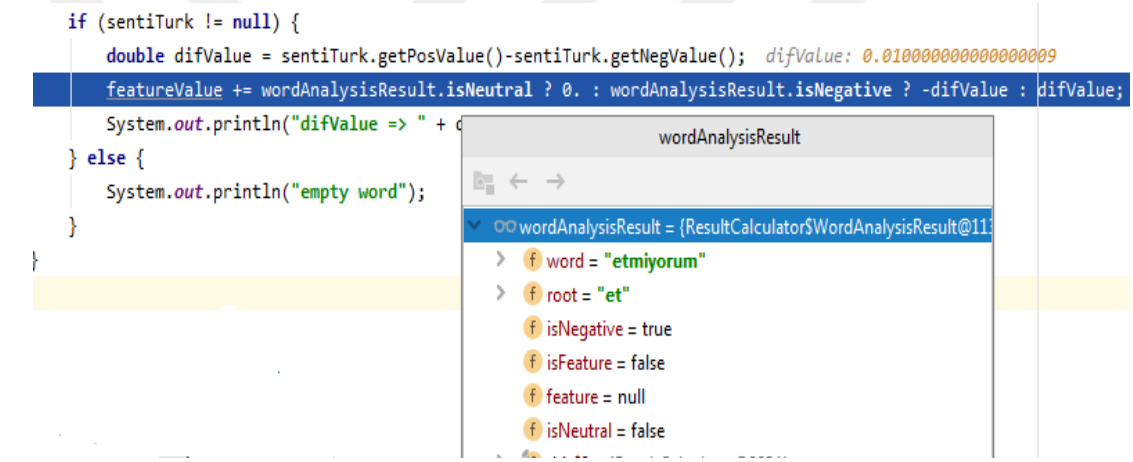

Figure 3.14 The example of ABSA for suffix "-me"

In reverse, sometimes negation suffixes make the word positive if the root of the word has a negative meaning in the Turkish language [99]. As can be seen in Figure 3.15, the suffix "-suz", which was deviated from "-sız" by changing vowel from high to low, converted the negative root "sorun-" to positive. The difference polarity value "-1.0" of the root "sorun-", which is obtained from SentiTurkNet, was multiplied by "-1" and then assigned to the corresponding aspect.

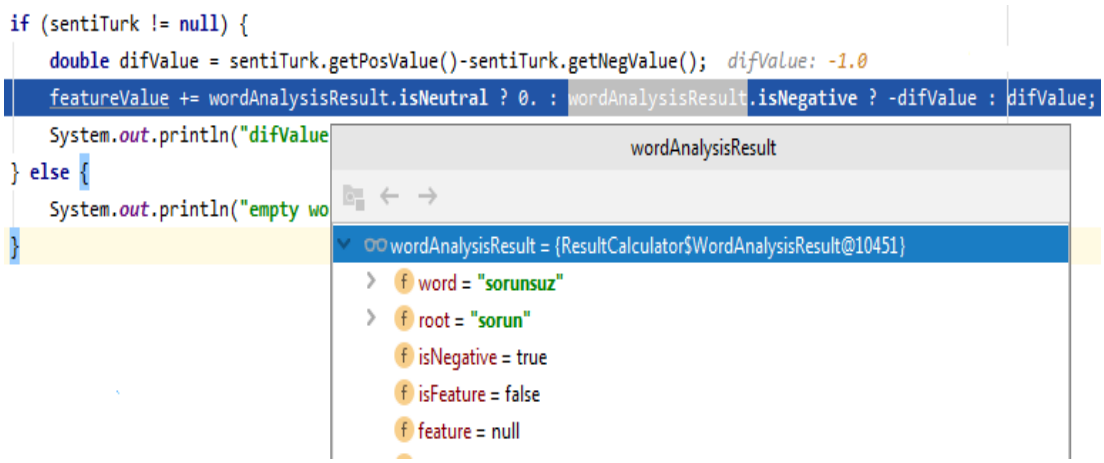

Figure 3.15 The example of ABSA for suffix "-suz"

Another issue which was needed to be analyzed separately was the usage of the word "fiyat (price)". "Yüksek (high)" word has a positive meaning in the Turkish language but becomes negative when it refers to the word "fiyat". Similarly, "düşük (low)" word has a negative meaning in Turkish but becomes positive when used with the word "fiyat". As can be seen in Figure 3.16, if the aspect previousFeature is the word "fiyat" and the root of the word is "yüksek", then the difference polarity value "0.54" of the root is multiplied by "-1" (Appendix C).

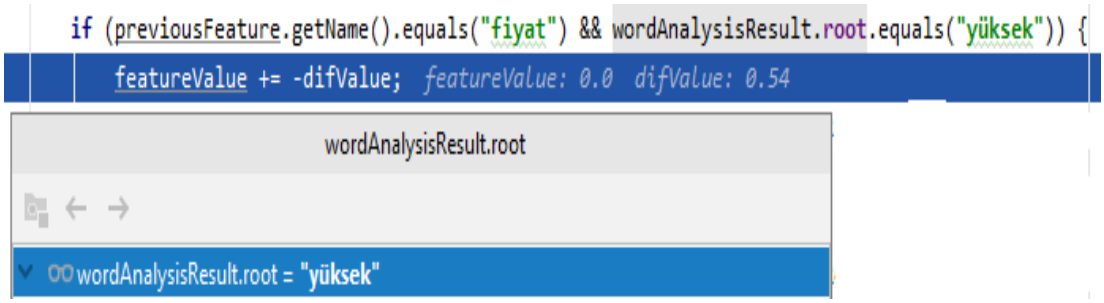

Figure 3.16 The usage of "fiyat" along with "yüksek"

Also, if the previousFeature is "fiyat" and the root of word is "düşük" word, then the difference polarity value "-1.0" of the root is multiplied by "-1" which can be seen in Figure 3.17 (Appendix C).

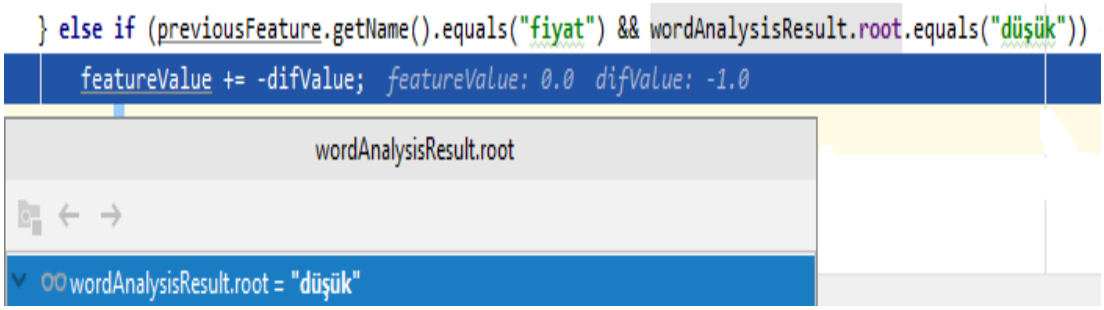

Figure 3.17 The usage of “fiyat” along with “düşük”

3.2.2.2 Word Group Level Aspect-Based Sentiment Analysis

In this thesis, word-group level aspect-based sentiment analysis is also implemented to increase the success of the system. “Ne… ne…” word groups need to be analyzed separately since, the sentence containing “ne… ne…” word groups can have either positivity or negativity. In this thesis, neutral polarity value was ignored for word-level aspect-based sentiment analysis in general for most of the words. However, “Ne… Ne…” word groups need to be analyzed in terms of neutral polarity. Because, as can be seen in Algorithm 3.3, if both first ”Ne” and the second “Ne” are positive, the feature or corresponding aspect is evaluated as negative, if both first ”Ne” and the second “Ne” are negative, the feature or corresponding aspect is evaluated as positive, and if one of them is positive or negative while the other one is the opposite, the word is then evaluated as neutral (Appendix C).

Algorithm 3.3 Ne… Ne… Case of Main Algorithm

Where
-x: the polarity of word or word group after the first ”ne”
-y: the polarity of word or word group after the second ”ne”

1: **if** $x > 0$ and $y > 0$
2: **return** *Negative*
3: **else if** $x > 0$ and $y < 0$
4: **return** *Neutral*
5: **else if** $x < 0$ and $y > 0$
6: **return** *Neutral*
7: **else if** $x < 0$ and $y < 0$

```
8:        return Positive
9:    end if
```

In addition, “değil” word converts the meaning of the previous word to opposite. In Figure 3.18, the comment includes words which are “memnun” and “değilim”. wordAnalysisResult object which is created as output of the morphology object for ”memnun” word can be seen in Figure 3.19. “memnun” has isNegative variable as false which means positivity.

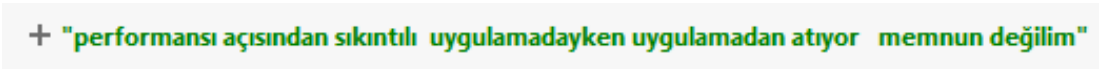

Figure 3.18 The example review

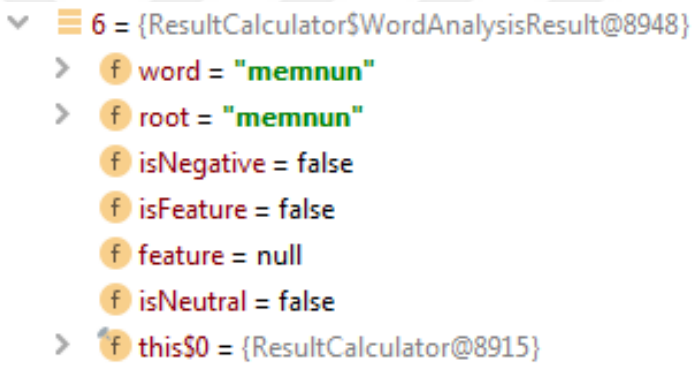

Figure 3.19 Word analysis of “memnun” word

As can be seen in Figure 3.20, when the root of word is “değil”, isNegative variable belong to the “memnun” word is reversed to true. The rules explained in Algorithm 3.4 are applied for the word “değil” (Appendix C).

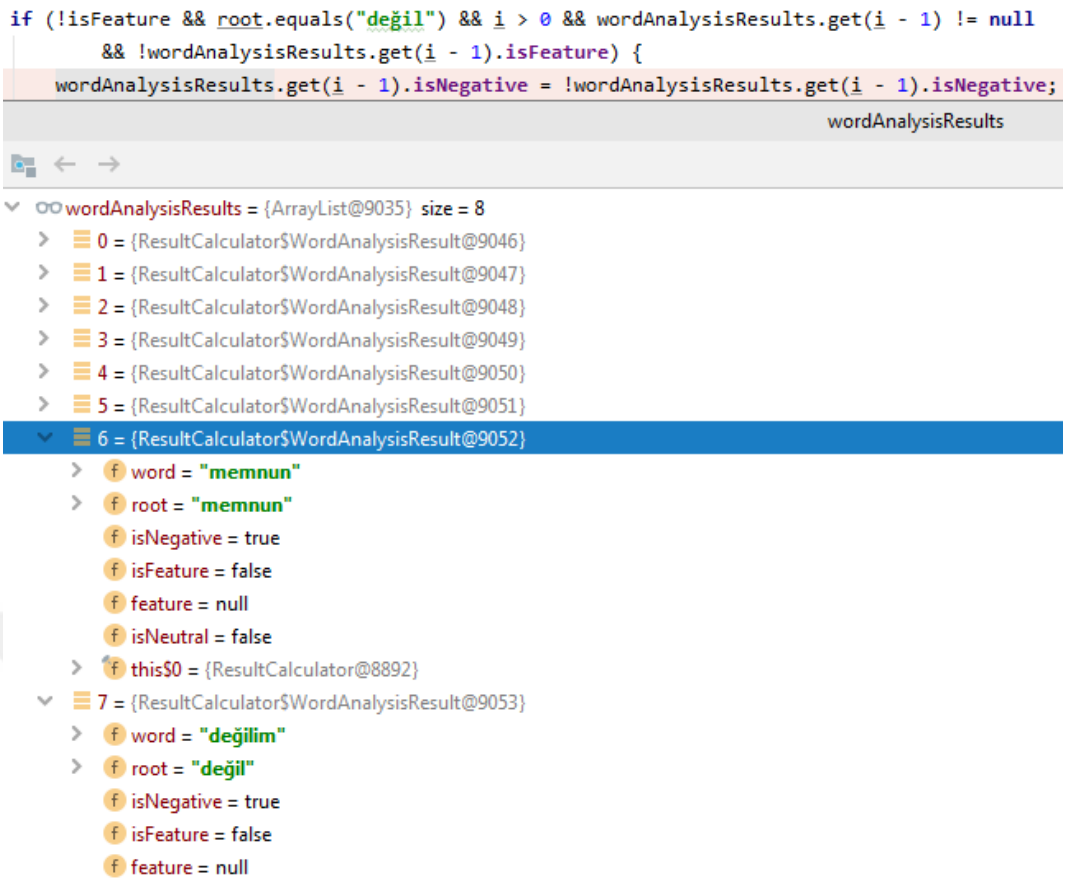

Figure 3.20 Labeled as negative to “memnun” word

Algorithm 3.4 Değil Case of Main Algorithm

Where

-x: the polarity of the word before ”Değil”

-y: the second word

1: **if** $x > 0$ and $y =$ ”*Değil*”

2: **return** *Negative*

3: **else if** $x = 0$ and $y =$ ”*Değil*”

4: **return** *Neutral*

5: **else if** $x < 0$ and $y =$ ”*Değil*”

6: **return** *Positive*

7: **end if**

CHAPTER 4
TEST AND EVALUATION

4.1 Test

In literature, computer-based [100] and human-based [27] analysis methods or their combinations resulting in hybrid systems are used commonly in the evaluation of aspect-based sentimental analysis of text. In this thesis, the human-based method is used to evaluate the performance of aspect-based sentiment classification. A confusion matrix is a table that is often used to describe the performance of a classification model on a set of test data for which the true values are known. As can be seen in Figure 4.1, the confusion matrix mainly is comprised of four values which are "true positive", "false positive", "true negative" and "false negative". "True positives" are the correctly predicted positive values which mean that the value of actual class is yes and the value of predicted class is also yes. "False positives" are the wrongly predicted positive values which means the value of actual class is no but the value of predicted class is yes. "True negatives" are the correctly predicted negative values which means the value of actual class is no and the value of predicted class is also no. "False negatives" are the wrongly predicted negative values which means the value of actual class is yes but the value of predicted class is no [101].

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Figure 4.1 Confusion Matrix [102]

In this study, 5483 reviews were collected by web scraping method. After removing the duplicate reviews, 5430 reviews remained. The system which was developed in this thesis performs an aspect-based sentiment analysis for Turkish iPhone reviews. 2193 reviews were selected for the 3 main aspects (kamera, performans, and fiyat)

and 13 corresponding features. Analysis results were tested 2 times. In the first pass, a total of 300 reviews were evaluated by people (Table 4.4). An example of the manual evaluation can be seen in Figure 4.2.

Results	Aspect	Comments	True Positive (TP)	False Positive (FP)	True Negatif (TN)	False Negatif (FN)
0,01	fiyat	Fiyatıyla, sorunsuz teslimatla herşeyiyle mükemmel. Teşekkürler hepsiburada	✓			
0,01	fiyat	fiyatı pahalı ama olsun sonuna kadar hakediyor.		✓		
-0,66	fiyat	Ürünü buradan almadım fakat gerçekten çok güzel,APPLE işi biliyor fakat çok pahalı! 4000-5000TL ne? Ucuzlamalı onun dışında sorun yok! Almanızı şiddetle tavsiye ederim (amerikadan)			✓	
-1,67	fiyat	Apple Türkiye garantili ,en düşük fiyat ve üstelik aynı gün içinde teslimat, başka ne istenir ki bir internet alışverişinde , Teşekkürler hepsiburada.com				✓

Figure 4.2 A manual test example

Confusion matrix of the first test can be seen in Table 4.1. When the reasons of the false analysis results were examined, the need for some improvements to increase the success of the system was realized. One of these improvements was adding words to SentiTurkNet which was an important issue for this thesis since lack of some words in SentiTurkNet were misleading in terms of aspect-based sentiment analysis. Words which were added to SentiTurkNet manually can be seen in Table 4.2

Table 4.1 Confusion matrix of the first test

Aspect name	**# of Reviews to be tested**	**True Positive (TP)**	**False Positive (FP)**	**True Negative (TN)**	**False Negative (FN)**
Kamera	100	68	10	14	8
Performans	100	61	13	19	7
Fiyat	100	68	16	10	6

Table 4.2 The words added to SentiTurkNet manually

Words Adding Manually to SentiTurkNet		
memnun	ucuz	harika
sıkıntılı	müthiş	sorun
sorunsuz	sorunlu	var
yok	yeterli	süper
yüksek	düşük	pahalı

Another improvement was made for the analysis of the word "fiyat" which is important for the domain of this system. While "yüksek", which is an adjective, makes meaning of a word positive; usage of "yüksek" with "fiyat" makes the polarity of "fiyat" negative. In reverse, while "düşük", which is an adjective, makes the meaning of a word negative; usage of "düşük" with "fiyat" makes the polarity of "fiyat" positive. Consequently, these exceptions were added to the implementation. After these improvements were completed, second test was done with 801 reviews. The improved results can be seen in Table 4.3.

Table 4.3 Confusion matrix of the second test

Aspect name	**# of Reviews to be tested**	**True Positive (TP)**	**False Positive (FP)**	**True Negative (TN)**	**False Negative (FN)**
Kamera	251	181	22	36	12
Performans	231	143	11	61	16
Fiyat	319	227	23	56	13

Table 4.4 Number of reviews

# of reviews collected using the web scraping method	5483
Remaining reviews after removing the duplicates	5430
# of reviews including aspects and features	2193
# of reviews which were tested for first time	300
# of reviews which were tested for second time	801

4.2 Evaluation

In this thesis, four measures which are precision, recall, F1-measure and accuracy were used for evaluation of performance of the system. Precision is a metric which quantifies the number of correct positive predictions made. Precision is calculated as the number of true positives divided by the total number of true positives and false positives. Recall is a metric that quantifies the number of correct positive predictions made out of all positive predictions that could have been made. Unlike precision that only comments on the correct positive predictions out of all positive predictions, recall provides an indication of missed positive predictions. Recall is calculated as the number of true positives divided by the total number of true positives and false negatives. Maximizing precision is appropriate for focusing on minimizing the number false positives, whereas maximizing the recall is appropriate for focusing on minimizing the number of false negatives. F1- measure is a metric which combines precision and recall as a single metric. Therefore, F1- measure is the more accurate metric when compared to precision and recall, which is calculated by multiplying precision, recall and 2, divided by the total number of precision and recall. In general, fourth metric to evaluate the performance is accuracy which is calculated as the number of true positive and true negative predictions divided by the total number of both true and false predictions. Accuracy is a great measure but only when values of false positive and false negatives are almost same [103]. However, our data set does not include symmetric false positive values and false negative values, therefore, accuracy is ignored in this thesis. The three metrics which were explained above was included to evaluation the performance of our system (Table 4.5).

Table 4.5 Evaluation Results

Aspects		**Precision**	**Recall**	**F1 Measure**
Kamera	positive	0.89	0.93	0.91
	negative	0.75	0.62	0.68
	average	0.82	0.78	0.80
Performans	positive	0.93	0.90	0.91
	negative	0.79	0.85	0.82
	average	0.86	0.88	0.87
Fiyat	positive	0.91	0.94	0.93
	negative	0.81	0.71	0.76
	average	0.86	0.83	0.85

Precision for “kamera” was evaluated as 0.82 which means that 82% of these were predicted correctly and 18% of these were predicted wrongly. When the reasons of wrong prediction were analyzed, some reasons were noticed. One of these was that a single review includes more than one feature or aspect. For example, “ancak videolar yeni ekran oranına göre henüz optimize edilmemiş bu biraz can sıkıcı” is one of the reviews in our data set. The review includes two features which are “video” and “ekran”. According to Algorithm 2 (Section 3.2.2.1) which was used for word-level sentiment analysis, once the word is detected as a feature, it is assumed that the sequent words refer to this feature and the polarity values of these words are added to the polarity value of features while the next feature word is detected. Therefore, in the example sentence, “yeni” has positive polarity and its value is added to “kamera” which is an aspect of “video”. On the other hand, in the rest of the sentence, “ekran” is detected as a new seperate feature and the following words after “ekran” were assumed to refer to “performans” aspect negatively. However, the example review includes the single feature “video” and all words in the review refer to “video” negatively. “Ekran” is not a feature in this review but it could only be understood by a human mind.

Recall measure for “kamera” was evaluated as 0.78 which means that 78% of these were predicted correctly as positive. 22% of these were incorrectly predicted as negative (False negative). One reason for these false negative reviews is that the algorithm automatically assumed that all the polarity words in the reviews refer to iPhone features. Because, in this thesis, it is assumed that there is no review which includes comparison of iPhone with other phones. For example, “note 8 in kamerasına daha fazla dayanamadım tekrar iphone a geri döndüm” is one of the reviews of our data set. “kamerasına” is the feature which is referred to by the word “dayanamadım” negatively. This evaluation is correct but “kamerasına” does not refer to “iphone”, referring to “note 8” instead. More comprehensive work is needed for the differentiation at product level. Another measure for “kamera” is the F1 metric which was found to be 0.80. The F1 metric is an important measure because of taking into account false positives as well as false negatives.

Precision measure for “performans” was evaluated as 0.86 which means that 86% of these were predicted correctly as positive. One of the reasons of the wrong prediction was that in the reviews, the sum of the polarity values of positive words may be higher than the sum of the polarity values of the negative words. An example from our data set is “şarjı gün gitmiyor çok kullanmadığım halde”. The feature is “şarjı” and the corresponding aspect is “performans”. In our system, the polarity value of each word is computed and their sum was assigned as the resulting polarity value of aspect or corresponding aspect of the feature. The total result which was computed for feature “şarjı” by our system is 0.060. The polarity value of “gün” is 0.01 and of “gitmiyor” is -0.01. Therefore, summation of these results in 0.0. Polarity values of the following words are 0.06, -0.01, and 0.01. Therefore, although the review indicated “şarjı” negatively in terms of semantic analysis, our system analyzed that the review had positive polarity value for aspect “performans”. This is the result of word-based semantic analysis relying solely on the polarity of individual words in a sentence. However, spoken languages have “multi-word phrases” with meanings different than the individual words composed them. Additionally, construction of sentence structure can also affect the meaning even though same word/phrases are used. Therefore, utilizing a sentiment analysis using word polarities can result in incorrect evaluation of a sentence if it contains phrases and/or have complex sentence structure.

Recall measure for “performans” is evaluated as 0.83 which means that 83% of these were predicted as positive correctly. One of the reasons of false negatives is ignoring neutral value into SentiTurkNet in this thesis. The example review is “10 numara 5 yıldız bataryası 4 gün gidiyor”. “4” has three polarity values which are positive, negative and neutral into SentiTurkNet. Neutral is the dominant value (0.818) among them, next is the negative value (0.125) and smallest is the positive value (0.057). The difference between the positive and negative values, which was used in our system for assigning polarity value to the word, is -0.068 which causes our system to evaluate “4” as negative. Owing to the fact that negative value is bigger than the summation of polarity values of words in the example review, the review is evaluated as negative. In future work, neutral value should be taken into account in

the evaluation of aspect-based semantic analysis to increase the success rates. Also, F1 measure for “performans” is 0.87.

The precision measure for “fiyat” is evaluated as 0.86 which means that 86% of these were predicted correctly as positive. As an incorrectly predicted example, in the review “babama fiyatını söyledim 5 bin daha katar araba alırız dedi”, even though the semantic analysis found it as positive based on the combined polarity value of each word taken from SentiTurkNet, the combined actual meaning is negative which is common in daily usage of Turkish language.

The recall measure for “fiyat” is evaluated as 0.94 which means that 94% of these were predicted as positive correctly. As an incorrectly predicted example, in the review “Bu fiyata başka bir yerde bulmak gerçekten zor, sipariş verdikten bir gün sonra elime ulaştı.Teşekkürler hepsiburada”, although the meaning is positive, it is evaluated as negative by our system. Because, word “zor” has a big negative polarity value which is higher than the summation of polarity values of each word taken from SentiTurkNet in the review. Also, F1 measure for “fiyat” is 0.85.

In Table 4.6, some evaluation results of the studies which performed aspect-based semantic analysis for Turkish can be seen. In 2016, Kama et al. proposed a web based feature extraction method to enhance performance metrics of the existing feature extraction methods for Turkish informal text. The results showed that precision, recall and F1 measures are 59.24%, 84.90% and 69.79%, respectively. In 2017, Kama et al. performed a system to match aspects (implicit, explicit) and sentiment words for Turkish informal text aiming to improve the performance results of ABSA systems. The evaluation results revealed that precision, recall and F1 measure were 91%, 80% and 85%, respectively. In 2019, Kama et al. developed a tool for ABSA. They used online product reviews as data sets and extracted the implicit and explicit aspects from the reviews with the frequency-based method. Then, they matched the aspects and sentiment words using three sentiment lexicons. The result showed that the values of precision and F1 measures improved compared to their previous studies. In 2016, Eryiğit performed a comprehensive study for ABSA of online Turkish reviews in two domains. The results of Turkish hotel

reviews were evaluated only with F1 measure which was found to be 72.64%. In 2017, Ekinci et al. proposed a method for the extraction of multi-word aspects. They used Turkish cell phones and hotel reviews for the evaluation of the proposed method. The evaluation results of cell phone reviews showed that precision and recall were 82% and 83%, respectively. As can be seen in Table 4.6, compared to the previously developed ABSA systems for Turkish, our system resulted with higher performance values for Recall and F1 measure.

Table 4.6 Example of evaluation results for Turkish ABSA studies

	Precision (%)	**Recall (%)**	**F1 Measure (%)**
Kama et al. [74]	59.24	84.90	69.79
Kama et al [41]	91	80	85
Kama et al. [73]	91.22	83.41	86.75
Eryiğit [28]	-	-	72.64
Ekinci et al.[42]	82	83	-
Our System	86	88	87

The reason for obtaining lower precision value was the impact of the negative sentiment analysis results to the overall average precision. Because, the majority of the negative reviews were written by using informal and slang words, and this reduces the success of sentiment analysis for negative comments. This is one of the biggest challenges encountered in sentiment analyses for negative reviews. However, in terms of positive reviews and their sentiment analysis, it can be seen that the precision obtained (between 91-93%) was comparatively higher than the other studies. One of the reasons for obtaining higher precision for positive reviews is that the normalization process was applied via Zemberek library. The version of Zemberek 16.0 allows the correction of mistypes or informal speech in the review via its normalization function. In this study, the normalization was applied as the first step of the data preprocessing. This helped the morphology function of Zemberek to analyze the roots and the suffixes of the words in the review correctly. Thus, the success of the algorithm to be implemented was increased. Moreover, additions of some words (Table 4.2) into SentiTurkNet also increased the precision of our system since the algorithms which are implemented for semantic analysis must find the

polarity values of words, especially the valuable words in terms of semantic analysis, from SentiTurkNet. Therefore, both the normalization and the word-additions increased the precision of our system by minimizing the false positive predictions.

On the other hand, the reason for obtaining higher recall values is the application of our algorithm for word group level sentiment analysis. Word groups can change the meaning of each word in the group. Therefore, some word groups should be taken into account in order to increase the success of the semantic analysis. In this study, “ne.. ne..”, “değil”, “yüksek” and “düşük” words were added into word group level algorithm for semantic analysis which increased the recall value by minimizing the false negative predictions.

Finally, since the F1 value is a combination of the precision and the recall value (Section 4.2), an increase in both values resulted in an increase in F1 value as well.

CHAPTER 5
CONCLUSION

In this thesis, aspect-based sentiment analysis of online reviews about iPhones in the Turkish language using the lexicon based approach has been implemented. The modules of the system namely, data gathering, preprocessing, feature extraction and sentiment analysis of the different aspects are explained in detail in the thesis. IPhone reviews which are used as the data set was retrieved from two web sites using the web scrapping method. Then, the data set was preprocessed with the use of the Zemberek library. The NLP tasks which were used to aim to process data were removing duplicate reviews, normalization, spell checking, removing punctuations and stop words as well as POS tagging. Another design issue which was taken into account was feature extraction explicitly and implicitly. Then, each feature was matched with the corresponding aspect manually. The main and last part of the design section was aspect-based sentiment analysis for which the Turkish lexicon (SentiTurkNet) was used. In the study, word and word-group level for aspect based sentiment analysis were considered. The results of aspect-based sentiment analysis were tested with the confusion matrix and recall, precision and F1 measure metrics were calculated twice. The highest value of precision, recall and F1 measure were 0.93, 0.94 and 0.93, respectively. The evaluation of our system resulted with higher values than other Turkish ABSA studies.

Some limitations were faced while conducting the aspect-based sentiment analysis in this thesis. One of these was that Turkish is a morphologically rich language for which there are limited number of NLP tools available. In morphologically rich languages, the root may be inflected by many different suffixes that may or may not change the meaning of the root. Therefore, the success of data preprocessing depends on the accuracy of the NLP tool used. Another limitation was that the polarity of words may change according to which words they are used with. For example, the word “yüksek” has a positive meaning when it is used with the word “performans” whereas it holds a negative meaning when used with the word “fiyat”. There are

many situations like this example which should be taken into account. However, the implementation of algorithms to handle these situations require significant amount of resources. The usage of the lexicon was also another limitation in this thesis. The effectiveness of aspect-based sentiment analysis depends on the accuracy of sentiment lexicon used which was limited in Turkish for the study conducted in this thesis. The final major limitation in this thesis was the writing style of some reviews that consists of informal as well as slang words used in daily communications. Since the polarity values of these types of words were not present in the sentiment lexicon used, the analysis for such reviews could not be conducted.

There are a limited number of studies about aspect-based sentiment analysis especially conducted with lexicon based methods for the Turkish language. In this context, our thesis has significant contribution to literature. Although the aspect-based sentiment analysis method which was proposed focused on only iPhone reviews, the GUI that was developed allows the users to add and delete explicit and implicit features and aspects independent from the domain. Domain independence feature of our approach also contributes to the literature.

In this thesis, the implicit and explicit features were extracted and grouped into the corresponding aspects manually. There are many methods to extract and group features proposed by other researchers most of which are statistical methods. In the statistical methods, some rules are generally applied to restrict the high frequency words in order to find the explicit features. However, the low frequency feature words are ignored in these methods. Finding them is an important task to extract implicit features. The association rule method is used to find the implicit features for grouping features into their corresponding aspects, some researchers used a lexicon such as WordNet to find the words' synonyms. As the future work, feature extraction and grouping methods mentioned above can be incorporated to our system.

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APPENDIX A

```
1  import urllib2
2  from bs4 import BeautifulSoup
3
4  URL= "https://www.hepsiburada.com/apple-iphone-6s-32-gb-apple-turkiye-garantili-p-HBV0000017G25-yorumlari"
5
6  # Query the website and return the html to the variable 'page'
7  page=urllib2.urlopen(URL)
8
9  # Parse the html in the 'page' variable, and store it in Beautiful Soup format
10 soup = BeautifulSoup(page, "html.parser")
11 review= soup.findAll("p",attrs={"class": "review-text"})
12
13 for pk in review:
14  name= pk.get_text()
15  print name
```

APPENDIX B

```
70  for (Comment comment : comments) {
71  try {
72              comment.setProduct(product);
73              comment.setNormalized(normalizer.normalize(comment.getRaw()));
74              System.out.println("Normalized => " + comment.getNormalized());
75              comment.setSpellChecked(spellCheck(comment.getNormalized()));
76              System.out.println("Spell Checked => " + comment.getSpellChecked());
77             comment.setPunctuationRemoved(StringUtil.removePunctuation(comment.getSpellChecked()));
78              System.out.println("Punctuation Removed => " + comment.getPunctuationRemoved());
79              comment.setStopWordsRemoved(removeStopWords(comment.getPunctuationRemoved()));
80              System.out.println("StopWords Removed => " + comment.getStopWordsRemoved());
81              commentRepository.save(comment);
82          } catch (Exception e) {
83              e.printStackTrace();
84          }
85      }
```

APPENDIX C

```
46  for (int i = 0; i < wordAnalyses.size(); i++) {
47      Feature detectedNewFeature = null;
48      boolean isNegativeWord = false;
49      List<SingleAnalysis> analysisResults = wordAnalyses.get(i).getAnalysisResults();
50      String root = wordAnalyses.get(i).getInput();
51      if (!analysisResults.isEmpty()) {
52          //root = analysisResults.get(0).getDictionaryItem().root;
53          root = analysisResults.get(0).getDictionaryItem().lemma;
54          for (SingleAnalysis.MorphemeData morphemeData : analysisResults.get(0).getMorphemeDataList()) {
55              if (morphemeData.morpheme.name.equals("Negative") ||
56  morphemeData.morpheme.name.equals("Without")) {
57                  isNegativeWord = !isNegativeWord;
58                  System.out.println("-------------------Negative WORD----------------------");
59              }
60          }
61      }
62
63      String finalRoot = root;
64      Optional<Feature> featureOpt = featureList.stream().filter(f ->
65  f.getName().equals(finalRoot)).findFirst();
66      if (featureOpt.isPresent()) {
67          detectedNewFeature = featureOpt.get();
68      } else {
69          Optional<FeatureDetail> featureDetailOpt = featureDetailList.stream().filter(f ->
70  f.getName().equals(finalRoot)).findFirst();
71
72          if (featureDetailOpt.isPresent()) {
73              detectedNewFeature = featureDetailOpt.get().getFeature();
74          }
75      }
```

```
76      boolean isFeature = detectedNewFeature != null;
77      wordAnalysisResults.add(new WordAnalysisResult(wordAnalyses.get(i).getInput(), root, isNegativeWord,
78  isFeature, detectedNewFeature));
79
80      if (!isFeature && root.equals("değil") && i > 0 && wordAnalysisResults.get(i - 1) != null
81              && !wordAnalysisResults.get(i - 1).isFeature) {
82          wordAnalysisResults.get(i - 1).isNegative = !wordAnalysisResults.get(i - 1).isNegative;
83      }
84
85
86      if (wordAnalyses.get(i).getInput().equals("ne")) {
87          isContainsNeWord++;
88      }
89  }
90
91  if (isContainsNeWord == 2) {
92      Boolean isPositiveFirstWord = null;
93      int firstWordIndex = 0;
94      for (int i = 0; i < wordAnalysisResults.size(); i++) {
95          if (wordAnalysisResults.get(i).word.equals("ne")) {
96              if (i + 1 < wordAnalysisResults.size() && wordAnalysisResults.get(i + 1) != null
97                      && !wordAnalysisResults.get(i + 1).isFeature) {
98                  if (isPositiveFirstWord == null) { // ilk "ne" den sonraki kelime
99                      SentiTurk sentiTurk = sentiTurkMap.get(wordAnalysisResults.get(i + 1).root);
100                     if (sentiTurk != null) {
101                         double difValue = sentiTurk.getPosValue() - sentiTurk.getNegValue();
102                         isPositiveFirstWord = difValue > 0;
103                         firstWordIndex = i + 1;
104                     }
105                 } else { // ikinci "ne" den sonraki kelime
106                     SentiTurk sentiTurk = sentiTurkMap.get(wordAnalysisResults.get(i + 1).root);
107                     if (sentiTurk != null) {
108                         double difValue = sentiTurk.getPosValue() - sentiTurk.getNegValue();
```

```
                        if ((difValue >= 0 && isPositiveFirstWord) || (difValue < 0 &&
!isPositiveFirstWord)) { // (+ ve +) veya (- ve -)
                            wordAnalysisResults.get(firstWordIndex).isNegative =
!wordAnalysisResults.get(firstWordIndex).isNegative;
                            wordAnalysisResults.get(i + 1).isNegative = !wordAnalysisResults.get(i +
1).isNegative;
                        } else { // + ve -
                            wordAnalysisResults.get(firstWordIndex).isNeutral = true;
                            wordAnalysisResults.get(i + 1).isNeutral = true;
                        }
                    }
                    break;
                }
            }
        }
    }
}

double featureValue = 0;
Feature previousFeature = null;

for (WordAnalysisResult wordAnalysisResult : wordAnalysisResults) {
    if (wordAnalysisResult.isFeature) { // feature
        System.out.println("feature detected => " + wordAnalysisResult.feature.getName());
        if (previousFeature != null) {
            Result result = new Result();
            result.setFeature(previousFeature);
            result.setComment(comment);
            result.setResult(featureValue);
            System.out.println("result => " + result.getResult());
            resultList.add(result);
            featureValue = 0;
        }
```

```
142
143         previousFeature = wordAnalysisResult.feature;
144         SentiTurk sentiTurk = sentiTurkMap.get(wordAnalysisResult.root);
145         if (sentiTurk != null) {
146             double difValue = sentiTurk.getPosValue()-sentiTurk.getNegValue();
147             featureValue += wordAnalysisResult.isNeutral ? 0. : wordAnalysisResult.isNegative ? -difValue :
148 difValue;}
149     } else { // sentiturk
150         SentiTurk sentiTurk = sentiTurkMap.get(wordAnalysisResult.root);
151         if (sentiTurk != null) {
152             double difValue = sentiTurk.getPosValue()-sentiTurk.getNegValue();
153             if (previousFeature != null) {
154                 if (previousFeature.getName().equals("fiyat") && wordAnalysisResult.root.equals("yüksek")) {
155                     featureValue += -difValue;
156                 } else if (previousFeature.getName().equals("fiyat") &&
157 wordAnalysisResult.root.equals("düşük")) {
158                     featureValue += -difValue;
159                 }
160                 else {
161                     featureValue += wordAnalysisResult.isNeutral ? 0. : wordAnalysisResult.isNegative ? -
162 difValue : difValue;
163                 }
164             }else{
165                 featureValue += wordAnalysisResult.isNeutral ? 0. : wordAnalysisResult.isNegative ? -
166 difValue : difValue;
167             }
168             System.out.println("difValue => " + difValue + " featureValue=> " + featureValue);
169         } else {
            System.out.println("empty word");
        }
    }
}
```

APPENDIX D

LIST OF STOP WORDS

acaba acep adamakıllı adeta ait altmış altı ama amma anca ancak arada artık aslında aynen ayrıca az açıkça açıkçası bana bari bazen bazı başkası başka belki ben benden beni benim beri beriki beş bilcümle bile bin binaen binaenaleyh bir biraz birazdan birbiri birden birdenbire biri birice birileri birisi birkaç birkaçı birlikte birçok birçoğu biteviye bittabi biz bizatihi bizce bizcileyin bizden bize bizi bizim bizimki bizzat boşuna bu buna bunda bundan bunlar bunları bunların bunu bunun burada buradan burası böyle böylece böylecene böylelikle böylemesine böylesine büsbütün bütün cümlesi da daha dahi dahil dahilen daima dair dayanarak de defa dek demin demincek deminden denli derakap derhal derken değil değin diye diğer diğeri doksan dokuz dolayı dolayısıyla doğru dört edecek eden ederek edilecek ediliyor edilmesi ediyor elbet elbette elli en enikonu epey epeyce epeyi esasen esnasında etmesi etraflı etraflıca etti ettiği ettiğini evleviyetle evvel evvela evvelce evvelden evvelemirde evveli eder eğer fakat filanca gah gayet gayetle gayri gayrı gelgelelim gene gerek gerçi geçende geçenlerde gibi gibilerden gibisinden göre gırla hakeza halbuki halen halihazırda haliyle handiyse hangi hangisi hani hariç hasebiyle hasılı hatta hele hem henüz hep hepsi her herhangi herkes herkesin hiç hiçbir hiçbiri hoş hulasaten iken iki ila ile ilen ilgili ilk illa illaki inen ise ister itibaren itibariyle itibarıyla iyice iyicene için iş işte kadar kaffesi kah kala kanımca karşın katrilyon kaynak kaçı kelli kendi kendilerine kendini kendisi kendisine kendisini kere kez keza kezalik keşke ki kim kimden kime kimi kimisi kimse kimsecik kimsecikler külliyen kırk kısaca kırk kısaca lakin lütfen madem mademki mamafih mebni meğer meğerki meğerse milyar milyon mu mü mi mı nasıl nasılsa nazaran naşi ne neden nedeniyle nedenle nedense nerde nerden nerdeyse nere nerede nereden neredeyse neresi nereye neye neyi neyse nice nihayet nihayetinde nitekim niye niçin o olan olarak oldu olduklarını oldukça olduğu olduğunu olmadı olmadığı olmak olması olmayan olmaz olsa olsun olup olur olursa oluyor on ona onca onculayın onda ondan onlar onlardan onları onların onu onun oracık oracıkta orada oradan oranca oranla oraya otuz oysa oysaki pek pekala peki pekçe peyderpey rağmen sadece sahi sahiden sana sanki sekiz seksen sen senden seni senin siz sizden sizi sizin sonra sonradan sonraları sonunda tabii tam tamam tamamen tamamıyla tarafından tek trilyon tüm var vardı vasıtasıyla ve velev velhasıl

velhasılıkelam veya veyahut ya yahut yakinen yakında yakından yakınlarda yalnız yalnızca yani yapacak yapmak yaptı yaptıkları yaptığı yaptığını yapılan yapılması yapıyor yedi yeniden yenilerde yerine yetmiş yine yirmi yok yoksa yoluyla yüz yüzünden zarfında zaten zati zira çabuk çabukça çeşitli çok çokları çoklarınca çokluk çoklukla çokça çoğu çoğun çoğunca çoğunlukla çünkü öbür öbürkü öbürü önce önceden önceleri öncelikle öteki ötekisi öyle öylece öylelikle öylemesine öz üzere üç şey şeyden şeyi şeyler şu şuna şunda şundan şunu şayet şey şeyden şeyi şeyler şu şuna şuncacık şunda şundan şunlar şunları şunu şunun şura şuracık şuracıkta şurası şöyle şayet şimdi şu şöyle